

# Asynchronous Carbon Sink Saturation in African and Amazonian Tropical Forests

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## Summary

Structurally intact tropical forests sequestered ~50% of global terrestrial carbon uptake over the 1990s and early 2000s, removing ~15% of anthropogenic CO<sub>2</sub> emissions<sup>1-3</sup>. Climate-driven vegetation models typically predict that this tropical forest ‘carbon sink’ will continue for decades<sup>4,5</sup>. Here, we assess trends in the carbon sink using 244 structurally intact African tropical forests spanning 11 countries, we compare them with 321 published plots from Amazonia and investigate the underlying drivers of the trends. The carbon sink in live aboveground biomass in intact African tropical forests has been stable for the three decades to 2015, at 0.66 Mg C ha<sup>-1</sup> yr<sup>-1</sup> (95% CI:0.53-0.79), in contrast to the long-term decline in Amazonian forests<sup>6</sup>. Thus, the carbon sink responses of Earth’s two largest expanses of tropical forest have diverged. The difference is largely driven by carbon losses from tree mortality, with no detectable multi-decadal trend in Africa and a long-term increase in Amazonia. Both continents show increasing tree growth, consistent with the expected net effect of rising atmospheric CO<sub>2</sub> and air temperature<sup>7-9</sup>. Despite the past stability of the African carbon sink, our data suggest a post-2010 increase in carbon losses, delayed compared to Amazonia, indicating asynchronous carbon sink saturation on the two continents. A statistical model including CO<sub>2</sub>, temperature, drought and forest dynamics accounts for the observed trends and indicates a long-term future decline in the African sink, while the Amazonian sink continues to rapidly weaken. Overall, the uptake of carbon into Earth’s intact tropical forests peaked in the 1990s. Given that the global terrestrial carbon sink is increasing in size, observations indicating greater recent carbon uptake into the Northern hemisphere landmass<sup>10</sup> reinforce our conclusion that the intact tropical forest carbon sink has already saturated. This tropical forest sink saturation and ongoing decline has consequences for policies to stabilise Earth’s climate.

177 **Main text**

178

179 Tropical forests account for approximately one-third of Earth's terrestrial Gross Primary Productivity  
180 and one-half of Earth's carbon stored in terrestrial vegetation<sup>11</sup>. Thus, small biome-wide changes in  
181 tree growth and mortality can have global impacts, either buffering or exacerbating the increase in  
182 atmospheric CO<sub>2</sub>. Models<sup>2,4,5,7,12</sup>, ground-based observations<sup>13-15</sup>, airborne atmospheric CO<sub>2</sub>  
183 measurements<sup>3,16</sup>, inferences from remotely sensed data<sup>17</sup>, and synthetic approaches<sup>3,8,18</sup> each suggest  
184 that, after accounting for land-use change, remaining structurally intact tropical forests (i.e. not  
185 impacted by direct anthropogenic impacts such as logging) are increasing in carbon stocks. This  
186 structurally intact tropical forest carbon sink is estimated at ~1.2 Pg C yr<sup>-1</sup> over 1990-2007 using  
187 scaled inventory plot measurements<sup>1</sup>. Yet, despite its policy relevance, changes in this key carbon  
188 sink remain highly uncertain<sup>19,20</sup>.

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190 Globally the terrestrial carbon sink is increasing<sup>2,7,8,21</sup>. Between 1990 and 2017 the land surface  
191 sequestered ~30% of all anthropogenic carbon dioxide emissions<sup>1,21</sup>. Rising CO<sub>2</sub> concentrations are  
192 thought to have boosted photosynthesis more than rising air temperatures have enhanced respiration,  
193 resulting in an increasing global terrestrial carbon sink<sup>2,4,7,8,21</sup>. Yet, for Amazonia, recent results from  
194 repeated censuses of intact forest inventory plots show a progressive two-decade decline in sink  
195 strength primarily due to an increase of carbon losses from tree mortality<sup>6</sup>. It is unclear if this simply  
196 reflects region-specific drought impacts<sup>22,23</sup>, or potentially chronic pan-tropical impacts of either  
197 heat-related tree mortality<sup>24,25</sup>, or internal forest dynamics resulting from past increases in carbon  
198 gains leaving the system<sup>26</sup>. A more recent deceleration of the rate of increase in carbon gains from  
199 tree growth is also contributing to the declining Amazon sink<sup>6</sup>. Again, it is not known if this is a  
200 result of either pan-tropical CO<sub>2</sub> fertilisation saturation, or rising air temperatures, or is merely a  
201 regional drought impact. To address these uncertainties, we (i) analyze an unprecedented long-term



202 inventory dataset from Africa, (ii) pool the new African and existing Amazonian records to  
203 investigate the putative environmental drivers of changes in the tropical forest carbon sink, and (iii)  
204 project its likely future evolution.

205

206 We collected, compiled and analysed data from structurally intact old-growth forests from the  
207 African Tropical Rainforest Observation Network<sup>27</sup> (217 plots) and other sources (27 plots) spanning  
208 the period 1968 to 2015 (Extended Data Figure 1; Supplementary Table 1). In each plot (mean size,  
209 1.1 ha), all trees  $\geq 100$  mm in stem diameter were identified, mapped and measured at least twice  
210 using standardised methods (135,625 trees monitored). Live biomass carbon stocks were estimated  
211 for each census date, with carbon gains and losses calculated for each interval (Extended Data Figure  
212 2).

213

#### 214 **Continental Carbon Sink Trends**

215 We detect no long-term trend in the per unit area African tropical forest carbon sink over three  
216 decades to 2015 (Figure 1). The aboveground live biomass sink averaged  $0.66 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$  (95%  
217 CI:  $0.53\text{--}0.79$ ;  $n=244$ ) and was significantly greater than zero for every year since 1990 (Figure 1).  
218 While very similar to past reports ( $0.63 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$ )<sup>13</sup>, this first estimate of the temporal trend in  
219 Africa contrasts with the declining Amazonian trend<sup>6</sup> (Figure 1). A linear mixed effect model shows  
220 a significant difference in the slopes of the sink trends for the two continents over the common time  
221 window (pooled data from both continents, common time window, 1983–2011.5;  $p=0.017$ ). Thus, the  
222 per unit area sink strength of the two largest expanses of tropical forest on Earth diverged in the  
223 1990s and 2000s.

224

225 The proximal cause of the divergent sink patterns is a significant increase in carbon losses (from tree  
226 mortality, i.e. the loss of carbon from the live biomass pool) in Amazonian forests, with no

detectable trend over three decades in African forests (Figure 1). A linear mixed effects model using pooled data shows a significant difference in slopes of carbon losses between the two continents over the common 1983-2011.5 time window ( $p=0.027$ ). Long-term trends in carbon gains (from tree growth and newly recruited trees) on both continents show significant increases (Figure 1), and we could detect no difference in slopes between the continents ( $p=0.348$ ; carbon gains from tree growth alone also show no continental difference in long-term trends,  $p=0.322$ ). However, an assessment of how underlying environmental drivers affect carbon gains and losses is needed to understand the ultimate causes of the divergent sink patterns.

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### 236 **Understanding the Carbon Sink Trends**

We first investigate environmental drivers exhibiting long-term change that impact theory-driven models of photosynthesis and respiration: atmospheric CO<sub>2</sub> concentration, surface air temperature, and water availability. A linear mixed effects model of carbon gains, with censuses nested within plots, and pooling the new African and published Amazonian data, shows a significant positive relationship with CO<sub>2</sub>, and significant negative relationships with mean annual temperature (MAT) and drought (measured as the Maximum Climatological Water Deficit, MCWD<sup>14</sup>; Figure 2; Extended Data Table 1). These results are consistent with a positive CO<sub>2</sub> fertilisation effect, and negative effects of higher temperatures and drought on tree growth, consistent with temperature-dependent increases in autotrophic respiration, and temperature- and drought-dependent reductions in carbon assimilation. By contrast, the equivalent model for carbon losses (i.e. tree mortality) shows no significant relationships with CO<sub>2</sub>, MAT or MCWD (Figure 2; Extended Data Table 1).

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We further investigate the responses of carbon gains and losses (for which the above analysis has no explanatory power) by expanding our potential explanatory variables to additionally include the change in environmental conditions (CO<sub>2</sub>-change, MAT-change, MCWD-change, see Extended Data

Figure 3 for calculation details), and two attributes of forests that may influence their response to the same environmental change: plot mean wood density (which in old-growth forests correlates with below-ground resource availability<sup>28,29</sup>), and the plot carbon residence time (which measures how long fixed carbon remains in the system, hence dictates when past increases in carbon gains leave the system as elevated carbon losses<sup>30</sup>).

The minimum adequate carbon gain model using our expanded explanatory variables (best ranked model using multimodel inference) has a positive relationship with CO<sub>2</sub>-change, and negative relationships with MAT, MAT-change, MCWD, and wood density (Table 2; model-average results are similar, see Methods and Supplementary Tables 2-4). The retention of both MAT and MAT-change suggests that higher temperatures correspond to lower tree growth, and that trees only partially acclimate to recently rising temperatures, which further reduces growth, consistent with warming experiments<sup>31</sup> and observations<sup>9</sup>. The inclusion of higher wood density, and it being related to lower carbon gains (Extended Data Figure 4), alongside no temporal trends in wood density (Extended Data Figure 5), suggests that old-growth forests with denser-wooded tree communities typically have fewer available below-ground resources, or such patterns may also emerge from disturbance regimes lacking large-scale exogenous events, consistent with prior studies<sup>26,28,32</sup>.

The minimum adequate carbon gain model using our expanded explanatory variables also highlights continental differences. Between 2000 and 2015 African forest carbon gains increased by 3.1% compared with a 0.1% decline in Amazonia over the same interval (Table 2). In Africa, from 2000 to 2015, the increase was composed of a 3.7% increase from CO<sub>2</sub>-change, partially offset by increasing droughts depleting gains by 0.5%, and only a slight decline in gains of 0.1% resulting from temperature increases (Table 2), because the rate of temperature change (MAT-change) decelerated over this time window (Extended Data Figure 5). For Amazonia, the same 3.7% increase due to CO<sub>2</sub>-

change was seen, while increasing droughts—and these forests’ greater sensitivity to drought—reduced gains by 2.7% (five times the impact in Africa), and temperature increases at the same rate as in the past (i.e. MAT-change is zero) further reduced gains by 1.1% (ten times the impact in Africa), leaving a net change in gains slightly below zero (Table 2). Thus, the recent stalling of carbon gain increases in Amazonia<sup>6</sup> is a response to drought and temperature and not due to an unexpected saturation of CO<sub>2</sub> fertilisation. Overall, the larger modelled increase in gains in Africa relative to Amazonia appear to be driven by slower warming, fewer or less extreme droughts, lower forest sensitivity to droughts, and overall lower temperatures (African forests are on average ~1.1°C cooler than Amazonian forests, as they typically grow at ~200 m higher elevation). Other continental differences may also be influencing the results, including higher nitrogen deposition in African tropical forests due to the seasonal burning of nearby savannas<sup>33</sup> and biogeographic history resulting in differing contemporary species pools and resulting functional attributes<sup>34,35</sup>.

The minimum adequate carbon loss model using our expanded explanatory variables shows higher losses with CO<sub>2</sub>-change and MAT-change, and lower losses with MCWD and the carbon residence time (CRT; Table 2). Thus, changes in carbon losses appear to be largely a function of carbon gains. First, the greater losses in forests with shorter CRT conform to a ‘high-gain high-loss’ forest dynamics pattern<sup>26</sup>. Second, wetter plots have a longer growing season and so have higher gains and correspondingly higher losses, explaining the negative relationship with MCWD. Third, as increasing CO<sub>2</sub> levels result in additional carbon gains, after some time these additional past gains leave the system resulting in greater carbon losses, explaining the positive relationship with CO<sub>2</sub>-change. Finally, in addition to these relationships with carbon gains, the inclusion of MAT-change ( $p < 0.001$ ) indicates heat- or vapour pressure deficit-induced tree mortality<sup>24</sup>. Overall, our results imply that chronic long-term environmental change factors, temperature and CO<sub>2</sub>, rather than simply

the direct effects of drought, underlie longer-term trends in tropical forest tree mortality, although other changes such as rising liana infestation rates seen in Amazonia<sup>36,37</sup> cannot be excluded.

The minimum adequate carbon loss model using our expanded explanatory variables replicates the continental trends (Figure 3). The overall lower loss rates in Africa reflect their longer CRT (69 yrs, 95% CI, 66-72), compared with Amazonian forests (56 yrs, 95% CI, 54-59) while over the 2000-2015 window the much smaller increase in loss rates in Africa compared to Amazonia results from a slower increase in warming and a stable CRT in Africa compared to continued warming at previous rates and a shortening CRT in Amazonian forests (Extended Data Figure 5). Furthermore, given that losses appear to lag behind gains they should relate to the long-term CRT of plots. This is what we find: the longer the CRT the smaller the increase in carbon losses, with no increase in losses for plots with  $CRT \geq 77$  years (Extended Data Figure 6). Consequently, due to the typically longer residence times of African forests, increasing losses in Africa ought to appear 10-15 years after the increase in Amazon losses began (*c.*1995). Strikingly, in Africa the most intensely monitored plots suggest that losses began increasing from *c.*2010 (Extended Data Figure 7), and plots with shorter CRT are driving the increase (Extended Data Figure 8). Thus, a mortality-dominated African carbon sink decline appears to have begun very recently.

### **Future of the Tropical Forest Carbon Sink**

Our carbon gain and loss models (Table 2) can be used to make a tentative estimate of the future size of the per unit area intact forest carbon sink (Figure 3). Extrapolations of the changes in the predictor variables from 1983-2015 forward to 2040 (Extended Data Figure 5) show declines in the sink on both continents (Figure 3). By 2030 the carbon sink in aboveground live biomass in intact African tropical forest is predicted to decline by 14% from the measured 2010-15 mean, to  $0.57 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$  ( $2\sigma$  range, 0.16-0.96; Figure 3). The Amazon sink continues to decline, reaching zero in 2035 ( $2\sigma$

range, 2011-2089; Figure 3). Our estimated sink strength on both continents in the 2020s and 2030s is sensitive to future CO<sub>2</sub> emissions pathways (CO<sub>2</sub>-change)<sup>38</sup>, resulting temperature increase (MAT, MAT-change) and hydrological changes (MCWD), plus changes in forest dynamics (CRT), but the sink is always lower than levels seen in the 2000s (see Methods and Supplementary Table 5). Thus, the carbon sink strength of the world's two most extensive tropical forests have now saturated, albeit asynchronously.

### Scaling Results to the Pan-tropics

Scaling our estimated mean sink strength by forest area for each continent signifies that Earth recently passed the point of peak carbon sequestration into intact tropical forests (Table 1). The continental sink in Amazonia peaked in the 1990s, followed by a decline, driven by sink strength peaking in the 1990s and a continued decline in forest area (Table 1). In Africa the per unit area sink strength peaked later in the 2000-2010 period, but the continental African sink peaked in the 1990s, due to the decline in forest area in the 2000s outpacing the small per unit area increase in sink strength. Including the modest uptake in the much smaller area of intact Asian tropical forest indicates that total pan-tropical carbon uptake peaked in the 1990s (Table 1). From peak pan-tropical intact forest uptake of 1.26 Pg C yr<sup>-1</sup> in the 1990s, we project a continued decline reaching just 0.29 Pg C yr<sup>-1</sup> in the 2030s (multi-decade decline of ~0.24 Pg C yr<sup>-1</sup> decade<sup>-1</sup>), driven by (i) reduced mean pan-tropical sink strength decline of 0.1 Mg C ha<sup>-1</sup> yr<sup>-1</sup> decade<sup>-1</sup> and (ii) ongoing forest area losses of ~13.5 million ha yr<sup>-1</sup> (see Extended Data Table 2 for forest area details). Critically, climate-driven vegetation model simulations have not predicted that peak net carbon uptake into intact tropical forests has already been passed<sup>2,4,5</sup>.

## Discussion

Our method of scaling to arrive at a pan-tropical sink estimate – in common with other studies using similar datasets<sup>1,6,13</sup> – is limited. Yet, pervasive net carbon uptake is expected given that we find a strong and ongoing CO<sub>2</sub> fertilisation effect. Using our CO<sub>2</sub> response in Table 2, we find an increase in aboveground carbon stocks of  $10.8 \pm 3.7$  Mg C ha<sup>-1</sup> 100 ppm<sup>-1</sup> CO<sub>2</sub>, or  $6.5 \pm 2.2\%$  ( $\pm$ SE; using an area-weighted pan-tropical mean aboveground C stock of 165 Mg C ha<sup>-1</sup>), comparable to the  $5.0 \pm 1.2\%$  increase in tropical forest C stocks 100 ppm<sup>-1</sup> CO<sub>2</sub> derived from a recent synthesis of CO<sub>2</sub> fertilisation experiments, despite a lack of data from mature tropical forests<sup>39</sup>. Our result is within the range of climate-driven vegetation models<sup>2,7</sup>, although it is greater than a number of recently-published models that include potential nutrient constraints, reported as  $5.9 \pm 4.7$  Mg C ha<sup>-1</sup> 100 ppm<sup>-1</sup> CO<sub>2</sub> (Ref.<sup>40</sup>). We find that the CO<sub>2</sub> fertilisation uptake is currently only partially offset by the negative impacts of similarly widespread rising air temperatures ( $-2.0 \pm 0.4$  Mg C ha<sup>-1</sup> °C<sup>-1</sup>, from Table 2), consistent with models<sup>7</sup>, limited experiments<sup>31</sup> and independent observations<sup>9</sup>, plus negative responses to drought<sup>41,42</sup>. Long-term and extensive increases in satellite-derived greenness in tropical regions not experiencing major changes in land-use management<sup>17,43</sup>, particularly in central Africa in the past decade<sup>44</sup>, indicate increases in tropical forest net primary productivity, providing further evidence that the sink is a widespread phenomenon<sup>44</sup>.

Nonetheless, our analyses show that this pervasive tropical forest sink in live biomass is in long-term decline, first saturating in Amazonia, and more recently followed by African forests, explaining the prior Africa-Amazon carbon sink divergence as part of a longer-term pattern of asynchronous saturation and decline. From an atmospheric perspective the full impacts of the contribution to the saturation of the sink from slowing carbon gains are experienced immediately, but the contribution from rising carbon losses is delayed because dead trees do not decompose instantaneously. Decomposition of this dead tree mass is ~50% in 4 yrs, and ~85% in 10 yrs, thus rising carbon losses

374 result in delayed carbon additions to the atmosphere<sup>45</sup>. Hence, from an atmospheric perspective the  
375 intact tropical forest biomass carbon sink likely peaked a few years later than our plot data indicate  
376 and the full impacts are not yet realised. The pan-tropical carbon sink in live biomass reduced by  
377 0.27 Pg C yr<sup>-1</sup> between the 1990s and 2000s (Table 1), but accounting for dead wood  
378 decomposition<sup>45</sup> shows a smaller 0.17 Pg C yr<sup>-1</sup> reduction from an atmospheric perspective (see  
379 Methods).

380

381 Given that the global terrestrial carbon sink is increasing, a weakening intact tropical forest sink  
382 implies that the extra-tropical carbon sink has increased over the past two decades. Independent  
383 observations of inter-hemispheric atmospheric CO<sub>2</sub> concentration indicates that carbon uptake into  
384 the Northern hemisphere landmass has increased at a greater rate than the global terrestrial carbon  
385 sink since the 1990s, with a further disproportionate increase in the 2000s<sup>10</sup>. The inter-hemispheric  
386 analysis suggests a weakening of the tropical forest sink by ~0.2 Pg C yr<sup>-1</sup> between the 1990s and  
387 2000s<sup>10</sup>, which is similar to the 0.17 Pg C yr<sup>-1</sup> weakening over the same time period that we find.  
388 This reinforces our conclusion that the intact tropical forest carbon sink has already saturated.

389

390 In summary, our results indicate that while intact tropical forests remain major stores of carbon and  
391 are key centres of biodiversity<sup>11</sup>, their ability to sequester additional carbon is waning. In the 1990s  
392 intact forests removed 17% of anthropogenic CO<sub>2</sub> emissions. This has declined to 6% in the 2010s,  
393 because the pan-tropical weighted average per unit area sink strength declined by 33%, forest area  
394 decreased by 19%, and CO<sub>2</sub> emissions increased by 46%. Although tropical forests are more  
395 immediately threatened by deforestation<sup>46</sup> and degradation<sup>47</sup>, and the future carbon balance will also  
396 depend on secondary forest dynamics<sup>48</sup> and forest restoration plans<sup>49</sup>, our analyses show that they are  
397 also impacted by atmospheric chemistry and climatic changes. Given that the intact tropical forest  
398 carbon sink is set to end sooner than even the most pessimistic climate-driven vegetation models



predict<sup>4,5</sup>, our analyses suggest that climate change impacts in the tropics may become more severe than predicted. Furthermore, the carbon balance of intact tropical forests will only stabilise once CO<sub>2</sub> concentrations and the climate stabilises.

Continued on-the-ground monitoring of the world's remaining intact tropical forests will be required to test our prediction that the intact tropical forest carbon sink will continue to decline. Such direct ground-based measurements also provide a constraint on estimating the size and location of the terrestrial carbon sink. In addition, our conclusion that tree mortality and internal forest dynamics are important controls on the future of the tropical forest carbon sink, may assist in improving the vegetation components of future Earth System Models<sup>50</sup> and contribute to reducing terrestrial carbon cycle feedback uncertainty<sup>19,20</sup>. Our findings also have policy implications. At the country-level: given intact tropical forests are a carbon sink, but the size is changing, national greenhouse gas reporting will require careful forest monitoring. At the international-level: given tropical forests are likely to sequester less carbon in the future than Earth System Models predict, an earlier date to reach net zero anthropogenic greenhouse gas emissions will be required to meet any given commitment to limit the global heating of Earth.

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641

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655

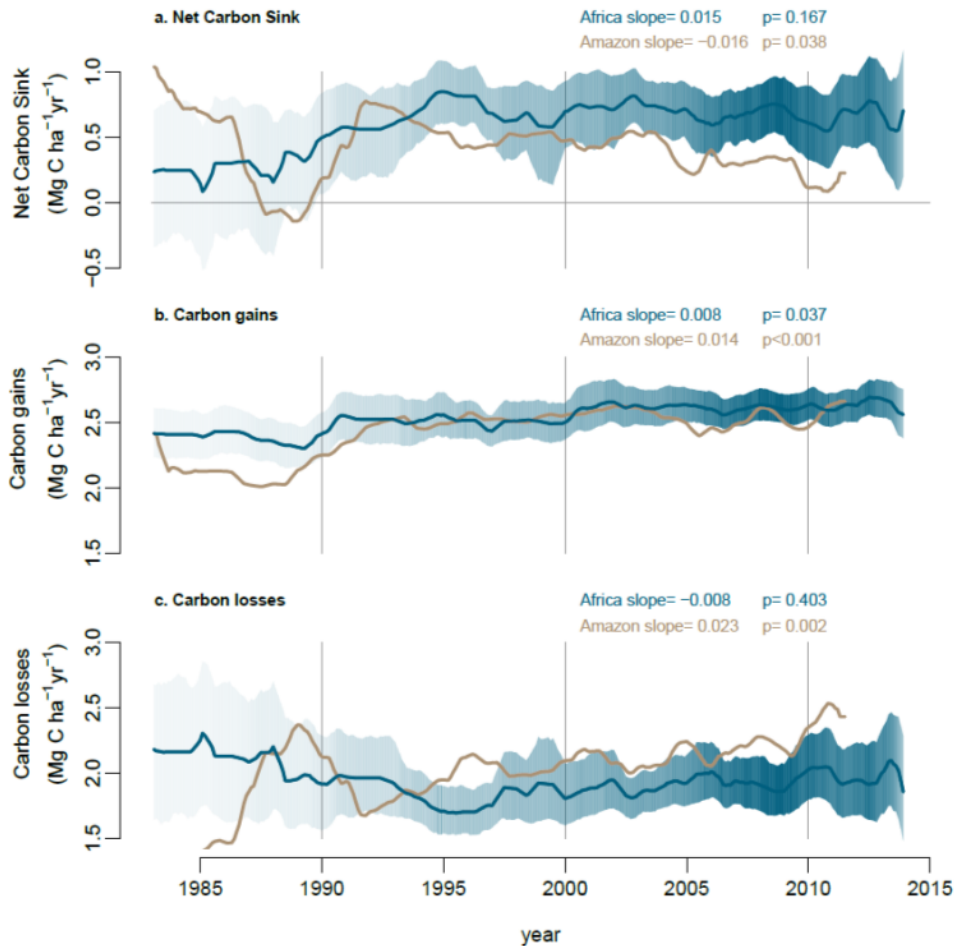
## 656 **Author Contributions**

657 S.L.L. conceived and managed the AfriTRON forest plot recensus programme, O.L.P., T.C.H.S.,  
658 L.J.T.W. and Y.M. contributed to its development. W.H., S.L.L., O.L.P., B.S. & M.J.P.S. developed  
659 the study. W.H., S.L.L., O.L.P., K.A.-B., H.B., A.C.-S., C.E.N.E., S.F., D.S., B.S., T.C.H.S., S.C.T.,  
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663 E.K.Y., E.K., D.K., M.E.L., J.A.L., J.L., J.C.L., J.-R.M., Y.M., A.R.M., J.M., E.H.M., F.M.M.,  
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666 J.V., L.J.T.W., S.W., H.W., J.T.W. and L.Z. contributed data (larger field contributions by S.L.L.,  
667 W.H., A.C.-S., B.S., H.T., A.K.D., C.E.N.E., J.M.M., K.A.-B. and S.F.). O.L.P., T.R.B., S.L.L. and  
668 G.L.-G. conceived and managed forestplots.net; O.L.P., T.R.B., S.L.L., E.G., G.L.-G., G.C.P., A.L.,  
669 R.J.W.B., T.R.F. and M.J.P.S. developed it. W.H., M.J.P.S., S.L.L., O.L.P., R.J.W.B., A.L., G.L.-G.,  
670 A.E.-M., A.K., E.G., T.R.B., A.C.B. and G.C.P. contributed analysis tools. W.H. and S.L.L. analysed  
671 the data (with important contributions from M.J.P.S.). S.L.L. and W.H. wrote the paper. All co-

672 authors read and approved the manuscript (with important insights provided by O.L.P., S.F.,  
673 R.J.W.B., E.G., H.B., D.S., M.J.P.S., S.G.-F., P.B., H.V. and S.C.T).

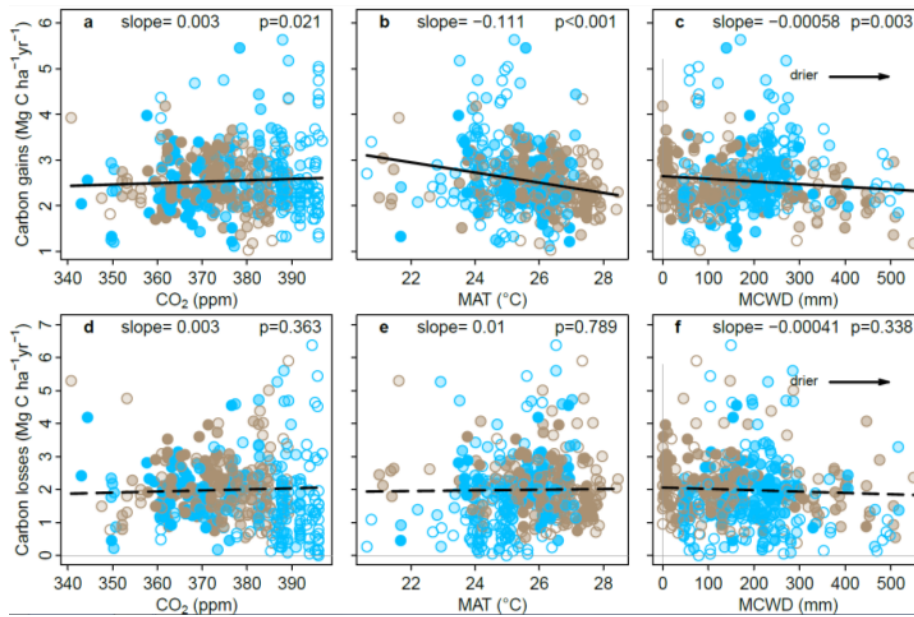
674

675 **Main Figures**

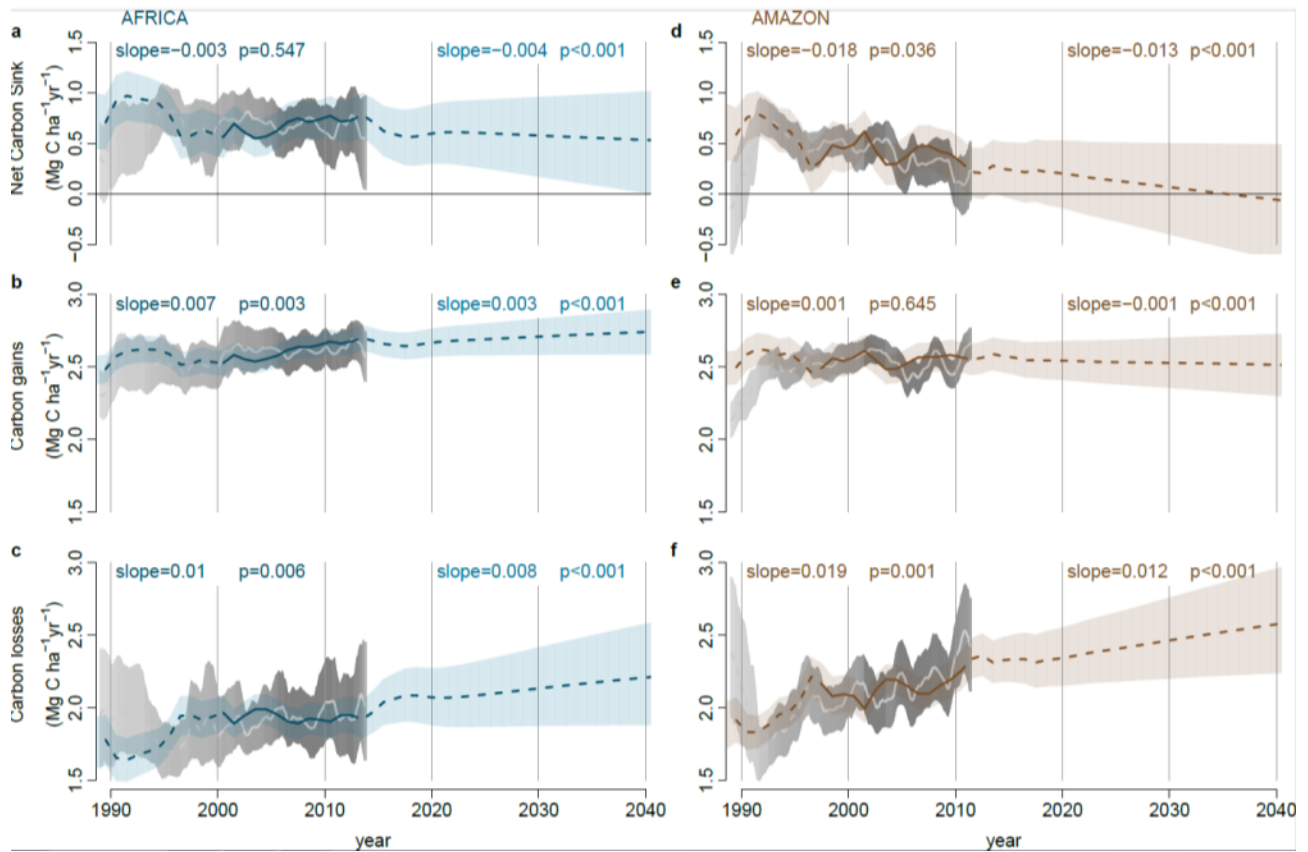


676

677 **Figure 1. Long-term carbon dynamics of structurally intact tropical forests in Africa (blue)**  
678 **and Amazonia (brown).** Trends in net aboveground live biomass carbon sink (a), carbon gains to  
679 the system from wood production (b), and carbon losses from the system from tree mortality (c),  
680 measured in 244 African inventory plots (blue lines) and contrasting published<sup>6</sup> Amazonian  
681 inventory data (brown lines; 321 plots). Shading corresponds to the 95% CI, with less transparent  
682 shading indicating a greater number of plots monitored in that year (most transparent: minimum 25  
683 plots monitored). The CI for the Amazonian dataset is omitted for clarity, but can be seen in Figure  
684 3. Slopes and p-values are from linear mixed effects models (see Methods).



**Figure 2. Potential environmental drivers of carbon gains and losses in structurally intact old-growth African and Amazonian tropical forests.** Aboveground carbon gains, from woody production (a-c), and aboveground carbon losses, from tree mortality (d-f), presented as time-weighted mean values for each plot, i.e. each census within a plot is weighted by its length, against the corresponding values of atmospheric carbon dioxide concentration (CO<sub>2</sub>), mean annual air temperature (MAT) and drought (as Maximum Climatological Water Deficit, MCWD), for African (blue) and Amazonian (brown) inventory plots. Each data point therefore represents an inventory plot, for visual clarity, and the level of transparency represents the total monitoring length, with empty circles corresponding to plots monitored for ≤ 5 years and solid circles for plots monitored for > 20 years. Solid lines show significant trends, dashed lines non-significant trends calculated using linear mixed effect models with census intervals (n=1566) nested within plots (n=565), using an empirically derived weighting based on interval length and plot area, on the untransformed pooled Africa and Amazon dataset (see Methods). Slopes and p-values are from the same linear mixed effects models. Carbon loss data and models are presented untransformed for comparison with carbon gains, but transformation is needed to fit normality assumptions; linear mixed effects models on transformed carbon loss data does not change the significance of the results, nor does including all three parameters and transformed data in a model (see Extended Data Table 1).



**Figure 3. Modelled past and future carbon dynamics of structurally intact tropical forests in Africa and Amazonia.** Predictions of net aboveground live biomass carbon sink (a,d), carbon gains (b,e), and carbon losses (c,f), for African (left panels) and Amazonian (right panels) plot inventory networks, based on CO<sub>2</sub>-change, Mean Annual Temperature, Mean Annual Temperature-change, drought (as Maximum Climatological Water Deficit), plot wood density, and plot carbon residence time, using observations in Africa until 2014 and Amazonia until 2011.5, and extrapolations of prior trends to 2040. Model predictions are in blue (Africa) and brown (Amazon), with solid lines spanning the window when  $\geq 75\%$  of plots were monitored to show model consistency with the observed trends, and shading showing upper and lower confidence intervals accounting for uncertainties in the model (both fixed and random effects) and uncertainties in the predictor variables. Light grey lines and grey shading are the mean and 95% CI of the observations from the African and Amazonian plot networks.

## Main Tables

**Table 1. Carbon sink in intact forests in Africa, Amazonia and the pan-tropics: 1980-2015 and predictions to 2040.** Mean values in bold, future predictions in italics, uncertainty in parentheses, 95% bootstrapped confidence intervals for 1980-2015, and 2σ for the predictions (2010-2040).

Period	No.		Per unit area aboveground live biomass C sink				Total C sink *		
			(Mg C ha <sup>-1</sup> yr <sup>-1</sup> )				(Pg C yr <sup>-1</sup> )		
	plots		Af. Am.	Africa	Amazon	Pan-tropics†	Africa	Amazon	Pan-tropics†
1980-1990	45	73	<b>0.33</b> (0.06-0.63)	<b>0.35</b> (0.06-0.59)	<b>0.35</b> (0.07-0.62)	<b>0.28</b> (0.05-0.53)	<b>0.49</b> (0.08-0.82)	<b>0.87</b> (0.16-1.52)	
1990-2000	96	172	<b>0.67</b> (0.43-0.89)	<b>0.53</b> (0.42-0.65)	<b>0.57</b> (0.39-0.74)	<b>0.50</b> (0.32-0.66)	<b>0.68</b> (0.54-0.83)	<b>1.26</b> (0.88-1.63)	
2000-2010	194	291	<b>0.70</b> (0.55-0.84)	<b>0.38</b> (0.26-0.48)	<b>0.50</b> (0.35-0.64)	<b>0.46</b> (0.37-0.56)	<b>0.45</b> (0.31-0.57)	<b>0.99</b> (0.70-1.25)	
2010-2015	184	172	<b>0.66</b> (0.40-0.91)	<b>0.24</b> (0.00-0.47)	<b>0.40</b> (0.15-0.65)	<b>0.40</b> (0.24-0.56)	<b>0.27</b> (0.00-0.52)	<b>0.73</b> (0.25-1.18)	
2010-2020 ‡	-	-	<b>0.63</b> (0.36-0.89)	<b>0.23</b> (-0.05-0.50)	<b>0.38</b> (0.11-0.65)	<b>0.37</b> (0.21-0.53)	<b>0.25</b> (-0.05-0.54)	<b>0.68</b> (0.17-1.16)	
2020-2030 ‡	-	-	<b>0.59</b> (0.24-0.93)	<b>0.12</b> (-0.29-0.51)	<b>0.30</b> (-0.08-0.67)	<b>0.31</b> (0.13-0.49)	<b>0.12</b> (-0.29-0.52)	<b>0.47</b> (-0.15-1.07)	
2030-2040 ‡	-	-	<b>0.55</b> (0.08-0.99)	<b>0.00</b> (-0.54-0.49)	<b>0.21</b> (-0.29-0.67)	<b>0.26</b> (0.04-0.47)	<b>0.00</b> (-0.50-0.46)	<b>0.29</b> (-0.46-0.97)	

\* Total Continental C sink is the per unit area aboveground C sink multiplied by intact forest area for 1990-2010 (from ref.<sup>1</sup>, see Extended Data Table 2) and continent specific extrapolations to 2040. Total Continental C sink includes continent-specific estimates of trees <100 mm DBH, lianas and roots (see Methods).

† Pan-tropical aboveground live biomass C sink is the area-weighted mean of African, Amazonian and Southeast Asian sink values. Southeast Asian values were from published per unit area carbon sink data<sup>15</sup> (n=49 plots) for 1990-2015, with 1980-1990 assumed to be the same as 1990-2000 due very low sample sizes. Pan-tropical total C sink is the sum of African, Amazonian and Southeast Asian total continental carbon sink values. The continental sink in Southeast Asia is a modest and declining contribution to the pan-tropical sink, due to the very small area of intact forest remaining, at 0.11, 0.08, 0.07 and 0.06 Pg C yr<sup>-1</sup> in the 1980s, 1990s, 2000s and 2010s, hence uncertainty in the Southeast Asian sink cannot reverse the pan-tropical declining sink trend.

‡ Per unit area total C sink for 2010-2020, 2020-2030 and 2030-2040 was predicted using parameters from Table 2, except for the 2010-2020 sink in Africa which is the mean of the measured sink from 2010-2015 and the modelled sink from 2015-2020. For the Asian sink we assumed the parameters as for Africa, as Asian forest median CRT is 61 years, close to African median, 63 years.

**Table 2. Minimum adequate models to predict carbon gains and losses in African and Amazonian tropical forests. These are the best ranked gains and loss models.** Where continental values differ, those for Africa are reported first, followed by Amazonian values.

Carbon gains, Mg C ha <sup>-1</sup> yr <sup>-1</sup>					
Predictor variable	Parameter value	Standard Error	t-value	p-value	2000-2015 change in gains (%) *
(Intercept)	5.255   5.395	0.603   0.614	8.7   8.8	<0.001	-
CO <sub>2</sub> -change (ppm yr <sup>-1</sup> ) †	0.238	0.096	2.5	0.013	3.69%   3.71%
MAT (°C)	-0.083	0.025	-3.3	0.001	-0.67%   -1.07%
MAT-change (°C yr <sup>-1</sup> ) ‡	-1.243	0.233	-5.3	<0.001	0.58%   0.00% §
MCWD (mm x1000)	-0.405   -1.391	0.381   0.24	-1.1   -5.8	0.289   <0.001	-0.52%   -2.73%
WD (g cm <sup>-3</sup> )	-1.295	0.530	-2.4	0.015	0.05%   0.00%
Carbon losses, Mg C ha <sup>-1</sup> yr <sup>-1</sup>					
Predictor variable	Parameter value	Standard Error	t-value	p-value	2000-2015 change in losses (%) *
(Intercept)	1.216	0.086	14.1	<0.001	-
CO <sub>2</sub> -change (ppm yr <sup>-1</sup> ) †	0.130	0.059	2.2	0.026	11.38%   14.81%
MAT-change (°C yr <sup>-1</sup> )	0.766	0.162	4.7	<0.001	-1.56%   0.00%
MCWD (mm x10000) ‡	-0.232	0.107	-2.2	0.030	-1.21%   -2.42%
CRT (yr)	-0.003	0.001	-6.1	<0.001	-0.57%   1.39%

\* The 2000-2015 change in gains/losses for each predictor variable was estimated allowing only the focal predictor to vary; this change was then expressed as a percentage of the annual gains/losses in the year 2000 allowing all predictors to vary.

† Change over the past 56 years.

‡ Change over the past 5 years.

§ A positive value for Africa indicates that MAT increased more slowly over 2000-2015 compared to the mean increase over 1983-2015, therefore contributing to an increase in gains; a zero value for Amazonia indicates that the rate of MAT increase was the same over 2000-2015 as the mean increase over 1983-2015.

|| Carbon loss values were normalized via power-law transformation,  $\lambda = 0.361$ .



## Online Methods

### Plot Selection

Closed canopy (i.e. not woody savanna) old-growth mixed-age forest inventory plots were selected using commonly used criteria<sup>6,13,27</sup>: free of fire and industrial logging; all trees with diameter at reference height  $\geq 100$  mm measured at least twice;  $\geq 0.2$  ha area;  $< 1500$  m.a.s.l. altitude; MAT  $\geq 20.0^{\circ}\text{C}$ <sup>51</sup>; annual precipitation  $\geq 1000$  mm<sup>51</sup>; located  $\geq 50$  m from anthropogenic forest edges. Of the 244 plots included in the study, 217 contribute to the African Tropical Rainforest Observatory Network (AfriTRON; [www.afritron.org](http://www.afritron.org)), with data curated at [www.ForestPlots.net](http://www.ForestPlots.net)<sup>52,53</sup>. These include plots from Sierra Leone, Liberia, Ghana, Nigeria, Cameroon, Gabon, Republic of Congo, Democratic Republic of Congo (DRC), Uganda and Tanzania<sup>52,53</sup> (Extended Data Figure 1). Fifteen plots are part of the TEAM network, from Cameroon, Republic of Congo, Tanzania, and Uganda<sup>54-57</sup>. Nine plots contribute to the ForestGEO network, from Cameroon and DRC<sup>58</sup> (9 plots from DRC, codes SNG, contribute to both AfriTRON and ForestGEO networks, included above in the AfriTRON total). Finally, three plots from Central African Republic are part of the CIRAD network<sup>59,60</sup>. The large majority of plots are sited in terra firme forests and have mixed species composition, although four are in seasonally flooded forest and 14 plots are in *Gilbertiodendron dewevrei* monodominant forest, a locally common forest type in Africa (Supplementary Table 1). The 244 plots have a mean size of 1.1 ha (median, 1 ha), with a total plot area of 277.9 ha. The dataset comprises 391,968 diameter measurements on 135,625 stems, of which 89.9% were identified to species, 97.5% to genus and 97.8% to family. Mean total monitoring period is 11.8 years, mean census length 5.7 years, with a total of 3,214 ha years of monitoring. The 321 Amazon plots are published and were selected using the same criteria<sup>6</sup>, except in the African selection criteria we specified a minimum anthropogenic edge distance and added a minimum temperature threshold.

777 **Plot Inventory and Tree Biomass Carbon Estimation**

778 Tree-level aboveground biomass carbon is estimated using an allometric equation with parameters  
779 for tree diameter, tree height and wood mass density<sup>61</sup>. The calculation of each is discussed in turn.  
780 All calculations were performed using the R statistical platform, version 3.2.1 (ref.<sup>62</sup>) using the  
781 BiomasaFP R package, version 0.2.1 (ref.<sup>63</sup>).

782

783 *Tree Diameter:* In all plots, all woody stems with  $\geq 100$  mm diameter at 1.3 m from the base of the  
784 stem ('diameter at breast height', DBH), or 0.5 m above deformities or buttresses, were measured,  
785 mapped and identified using standard forest inventory methods<sup>64,65</sup>. The height of the point of  
786 measurement (POM) was marked on the trees and recorded, so that the same POM is used at the  
787 subsequent forest census. For stems developing deformities or buttresses over time that could  
788 potentially disturb the initial POM, the POM was raised approximately 500 mm above the deformity.  
789 Estimates of the diameter growth of trees with changed POM used the ratio of new and old POMs, to  
790 create a single trajectory of growth from the series of diameters at two POM heights<sup>6,13,65</sup>. We used  
791 standardised protocols to assess typographical errors and potentially erroneous diameter values (e.g.  
792 trees shrinking by  $>5$  mm), missing values, failures to find the original POM, and other issues.  
793 Where necessary we estimated the likely value via interpolation or extrapolation from other  
794 measurements of that tree, or when this was not possible we used the median growth rate of trees in  
795 the same plot, census and size-class, defined as DBH = 100-199 mm, or 200-399 mm, or  $>400$  mm<sup>65</sup>.  
796 We interpolated measurements for 1.3% of diameters, extrapolated 0.9%, and used median growth  
797 rates for 1.5%.

798

799 *Tree height:* Height of individuals from ground to the top leaf, hereafter  $H_t$ , was measured in 204  
800 plots, using a laser hypsometer (Nikon forestry Pro) from directly below the crown (most plots), a  
801 laser or ultrasonic distance device with an electronic tilt sensor, a manual clinometer, or by direct

measurement, i.e. tree climbing. Only trees where the top was visible were selected<sup>66</sup>. In most plots,  
 tree selection was similar: the 10 largest trees were measured, together with 10 randomly selected  
 trees per diameter from five classes: 100-199 mm, 200-299 mm, 300-399 mm, 400-499 mm, and  
 500+ mm trees, following standard protocols<sup>66</sup>. We measured actual height of 24,270 individual trees  
 from 204 plots. We used these data and the local.heights function in R package BiomasaFP<sup>63</sup> to fit 3-  
 parameter Weibull relationships:  $H_t = a \times (1 - e^{(-b \times (DBH/10)^c)})$  (equation 1). We chose the Weibull  
 model as it is known to be robust when a large number of measurements are available<sup>66,67</sup>. We  
 parameterised separate  $H_t$ -DBH relationship for four different combinations of edaphic forest type  
 and biogeographical region: (i) terra firme forest in West Africa, (ii) terra firme forest in Lower  
 Guinea and Western Congo Basin, (iii) terra firme forest in Eastern Congo Basin and East Africa,  
 (iv) seasonally flooded forest from Lower Guinea and Western Congo Basin (there were no  
 seasonally flooded forest plots in the other biogeographical regions). The parameters are: (i) terra  
 firme forest in West Africa,  $a=56.0$ ;  $b=0.0401$ ;  $c=0.744$ ; (ii) terra firme forest in Lower Guinea and  
 Western Congo Basin,  $a=47.6$ ;  $b=0.0536$ ;  $c=0.755$ ; (iii) terra firme forest in Eastern Congo Basin  
 and East Africa,  $a=50.8$ ;  $b=0.0499$ ;  $c=0.706$ ; and finally (iv) seasonally flooded forest from Lower  
 Guinea and Western Congo Basin,  $a=38.2$ ;  $b=0.0605$ ;  $c=0.760$ . For each of these combinations of  
 forest type and bioregion, the local.heights function combines all height measurements from all plots  
 belonging to that forest type/bioregion and fits the Weibull model parameters using non-linear least  
 squares (nls function in R with default settings), with starting values of  $a = 25$ ,  $b = 0.05$  and  $c = 0.7$   
 chosen as they led to regular model convergence. We fitted these models either treating each  
 observation equally or with case weights proportional to each trees' basal area. These weights give  
 more importance to large trees during model fitting. We selected the best fitting of these models,  
 determining this as the model that minimised prediction error of stand biomass when calculated with  
 estimated heights or observed heights. The parameters were used to estimate  $H_t$  from DBH for all  
 tree DBH measurements for input into the allometric equation. Mean measured individual total tree

827 height is 20.5 m; the height range is 1.5 to 72.5 m. The root mean squared error (RMSE) between the  
828 full dataset of measured heights and the predicted heights, is 5.7 m, which is 8.0% of the total range.  
829 Furthermore, RMSE is 5.3 m in terra firme forest in West Africa (7.5% of the range; n=9771 trees);  
830 RMSE is 6.4 m in terra firme forest in Lower Guinea and Western Congo Basin (8.7% of the range;  
831 n=10,838 trees); RMSE is 4.8 m in terra firme forest in Eastern Congo Basin and East Africa (8.8%  
832 of the range; n=3269 trees); and RMSE is 4.1 m in seasonally flooded forest from Lower Guinea and  
833 Western Congo Basin (12.5% of the range; n=392 trees).

834

835 *Wood Density:* Dry wood density ( $\rho$ ) measurements were compiled for 730 African species from  
836 published sources and stored in [www.ForestPlots.net](http://www.ForestPlots.net); most were sourced from the Global Wood  
837 Density Database on the Dryad digital repository ([www.datadryad.org](http://www.datadryad.org))<sup>68,69</sup>. Each individual in the  
838 tree inventory database was matched to a species-specific mean wood density value. Species in both  
839 the tree inventory and wood density databases were standardized for orthography and synonymy  
840 using the African Plants Database ([www.ville-ge.ch/cjb/bd/africa/](http://www.ville-ge.ch/cjb/bd/africa/)) to maximize matches<sup>13</sup>. For  
841 incompletely identified individuals or for individuals belonging to species not in the  $\rho$  database, we  
842 used the mean  $\rho$  value for the next higher known taxonomic category (genus or family, as  
843 appropriate). For unidentified individuals, we used the mean wood density value of all individual  
844 trees in the plot<sup>13,52</sup>.

845

846 *Allometric equation:* For each tree we used a published allometric equation<sup>61</sup> to estimate  
847 aboveground biomass. We then converted this to carbon, assuming that aboveground carbon (AGC)  
848 is 45.6% of aboveground biomass<sup>70</sup>. Thus:  $AGC = 0.456 \times (0.0673 \times (\rho \times (DBH/10)^2 \times H_t)^{0.976}) / 1000$   
849 (equation 2), with DBH in mm, dry wood density,  $\rho$ , in g cm<sup>-3</sup>, and total tree height,  $H_t$ , in m (ref.<sup>61</sup>).

850

851 *Aboveground Carbon* (AGC, in Mg C ha<sup>-1</sup>) in living biomass for each plot at each census date was  
852 estimated as the sum of the AGC of each living stem, divided by plot area (in hectares).

853

#### 854 **Carbon Gain and Carbon Loss estimation**

855 *Net Carbon Sink* (in Mg C ha<sup>-1</sup> yr<sup>-1</sup>) is estimated as carbon gains minus carbon losses. Calculation  
856 details are explained below.

857

858 *Carbon Gains* (in Mg C ha<sup>-1</sup> yr<sup>-1</sup>) are the sum of the aboveground live biomass carbon additions from  
859 the growth of surviving stems and the addition of newly recruited stems, divided by the census  
860 length (in years) and plot area (in hectares). For each stem that survived a census interval, carbon  
861 additions from its growth (Mg C ha<sup>-1</sup> yr<sup>-1</sup>) were calculated as the difference between its AGC at the  
862 end census of the interval and its AGC at the beginning census of the interval. For each stem that  
863 recruited during the census interval (i.e. reaching DBH $\geq$ 100 mm), carbon additions were calculated  
864 in the same way, assuming DBH=0 mm at the start of the interval<sup>65</sup>. *Carbon Losses* (in Mg C ha<sup>-1</sup> yr<sup>-1</sup>)  
865 are estimated as the sum of aboveground biomass carbon from all stems that died during a census  
866 interval, divided by the census length (in years) and plot area (in hectares). Both carbon gains and  
867 carbon losses are calculated using standard methods<sup>6</sup>, including a census interval bias correction,  
868 using the SummaryAGWP function of R-package BiomasaFP<sup>63,64,68</sup>.

869

870 As carbon gains are affected by a census interval bias, with the underestimate increasing with census  
871 length, we corrected this bias by accounting for (i) the carbon additions from trees that grew before  
872 they died within an interval (unobserved growth) and (ii) the carbon additions from trees that  
873 recruited and then died within the same interval (unobserved recruitment)<sup>65,71</sup>.

874

875 Component (i), the unobserved growth of a stem that died during a census interval, is estimated as  
 876 the difference between AGC at death and AGC at the start of the census. These are calculated using  
 877 equation 2, from respectively  $DBH_{\text{death}}$  and  $DBH_{\text{start}}$ . The latter is part of the data, the first can be  
 878 estimated as:  $DBH_{\text{death}} = DBH_{\text{start}} \times G \times Y_{\text{mean}}$ , where  $G$  is the plot-level median diameter growth rate  
 879 ( $\text{mm yr}^{-1}$ ) of the size class the tree was in at the start of the census interval (size classes are defined  
 880 as  $D < 200 \text{ mm}$ ,  $200 \text{ mm} < D \leq 400 \text{ mm}$  and  $D > 400 \text{ mm}$ ) and  $Y_{\text{mean}}$  is the mean number of years  
 881 trees survived in the census interval before dying.  $Y_{\text{mean}}$  is calculated from the number of trees that  
 882 are expected to have died in each year of the census interval, which is derived from the plot-level  
 883 per-capita mortality rate ( $m_a$ ; % dead trees  $\text{yr}^{-1}$ ) calculated following equation 5 in ref.<sup>71</sup>.

884

885 Component (ii), growth of recruits that were not observed because they died during the census  
 886 interval, is estimated by calculating the number of unobserved recruits and diameter at death for each  
 887 unobserved recruit. The number of unobserved recruits ( $\text{stems ha}^{-1} \text{yr}^{-1}$ ) is estimated as:  $N_{u,r} = R_a -$   
 888  $P_{\text{surv}} \times R_a$ , where  $R_a$  ( $\text{recruited stems ha}^{-1} \text{yr}^{-1}$ ) is the per area annual recruitment calculated following  
 889 equation 11 in ref.<sup>71</sup> and  $P_{\text{surv}}$  is the probability of each recruit surviving until the next census:  $P_{\text{surv}} =$   
 890  $(1 - m_a)^T$ , where  $T$  is the number of years remaining in the census interval. Summing  $N_{u,r}$  for each year  
 891 in a census interval gives the total number of unobserved recruits in that census interval. We then  
 892 estimate diameter at death for each unobserved recruit, which is given in mm by  $DBH_{\text{death},u,r} = 100 +$   
 893  $(G_s \times Y_{\text{mean-rec}})$ , where  $G_s$  is the plot-level median diameter growth rate ( $\text{mm yr}^{-1}$ ) of the smallest size  
 894 class (i.e.  $D < 200 \text{ mm}$ ) and  $Y_{\text{mean-rec}}$  is the mean life-span of unobserved recruits calculated as the  
 895 mean life-span of recruits in a given year, weighted by  $N_{u,r}$ . The mean life-span of recruits in a given  
 896 year is calculated from the number of recruits that died in that year, which is derived from the plot-  
 897 level per-capita mortality rate ( $m_a$ ; % dead trees  $\text{yr}^{-1}$ ). Growth of each unobserved recruit ( $\text{mm yr}^{-1}$ ) is  
 898 then calculated as  $DBH_{\text{death},u,r}$  divided by  $Y_{\text{mean-rec}}$ .

899

900 The census interval bias correction (components i and ii together) typically add <3% to plot-level  
901 carbon gains. Carbon Losses are affected by the same census interval bias, hence we corrected this  
902 bias by accounting for (i) the additional carbon losses from the trees that were recruited and then  
903 died within the same interval, and (ii) the additional carbon losses resulting from the growth of the  
904 trees that died in the interval<sup>6,15,63</sup>. These two components are calculated in the same way as for  
905 Carbon gains and typically add <3% to plot-level carbon losses.

906

907 Carbon gains include both gains from the growth of surviving stems and new recruits. Separating  
908 carbon gains from tree growth of surviving stems and newly recruited stems, shows that carbon gains  
909 from recruitment are small overall, and are significantly lower in Africa than in the Amazon, likely  
910 due to the lower stem turnover rates and longer carbon residence time (Africa: 0.17 Mg C ha<sup>-1</sup> yr<sup>-1</sup>;  
911 CI: 0.16-0.18 versus Amazon: 0.27 Mg C ha<sup>-1</sup> yr<sup>-1</sup>; CI: 0.25-0.28, p<0.001; two-way Wilcoxon test),  
912 but this is compensated by carbon gains from survivors being significantly larger in Africa (2.33 Mg  
913 C ha<sup>-1</sup> yr<sup>-1</sup>; CI: 2.27-2.39) than in the Amazon (2.13 Mg C ha<sup>-1</sup> yr<sup>-1</sup>; CI: 2.09-2.17, p=0.014).  
914 Therefore, gains overall (sum of gains from surviving stems and newly recruited stems) are  
915 indistinguishable between the continents (Africa: 2.57 Mg C ha<sup>-1</sup> yr<sup>-1</sup>; CI: 2.51-2.67 vs Amazon: 2.46  
916 Mg C ha<sup>-1</sup> yr<sup>-1</sup>; CI: 2.41-2.50, p=0.460; two-way Wilcoxon test).

917

#### 918 **Long-term Gain, Loss and Net Carbon Sink Trend Estimation, 1983-2014**

919 The estimated mean and uncertainty in carbon gains, carbon losses and the net carbon sink of the  
920 African plots from 1983-2014 (Figure 1, Extended Data Figure 7 and Extended Data Figure 8) were  
921 calculated following ref.<sup>6</sup> to allow direct comparison with published Amazonian results. First, each  
922 census interval value was interpolated for each 0.1-yr period within the census interval. Then, for  
923 each 0.1-yr period between 1983 and 2014, we calculated a weighted mean of all plots monitored at

924 that time, using the square root of plot area as a weighting factor<sup>6</sup>. Confidence intervals for each 0.1-  
925 yr period were bootstrapped.

926

927 Trends in carbon gains, losses and the net carbon sink over time were assessed using linear mixed  
928 effects models (lmer function in R, lme4 package<sup>72</sup>), providing the linear slopes reported in Figure 1.  
929 These models regress the mid-point of each census interval against the value of the response variable  
930 for that census interval. Plot identity was included as a random effect, i.e. assuming that the intercept  
931 can vary randomly among plots. We did not include slope as a random effect, consistent with  
932 previously published Amazon analyses<sup>6</sup>, because models did not converge due to some plots having  
933 too few census intervals. Observations were weighted by plot size and census interval length.  
934 Weightings were derived empirically, by assuming *a priori* that there is no significant relation  
935 between the net carbon sink and census interval length or plot size, following ref.<sup>13</sup>. The following  
936 weighting removes all pattern in the residuals:  $\text{Weight} = \sqrt[3]{\text{length}_{\text{int}}} + \sqrt[4]{\text{plotsize}} - 1$  (equation 3),  
937 where  $\text{length}_{\text{int}}$  is the length of the census interval, in years. Significance was assessed by regressing  
938 the residuals of the net carbon sink model against the weights ( $p=0.702$ ).

939

940 Differences in long-term slopes between the two continents for carbon gains, carbon losses and net  
941 carbon sink, reported in the main text, were also assessed using linear mixed effects models, as  
942 described above, but performed on the combined African and Amazonian datasets and limited to  
943 their common time window, 1983 to 2011.5. For these three tests on the pooled data we included an  
944 additional interaction term between census interval date and continent, where a significant  
945 interaction would indicate that the slopes differ between continents. The statistical significance of  
946 continental differences in slope were assessed using the F-statistic (Anova function in R, car  
947 package<sup>73</sup>). Shortening the common time window to the 20 years when the continents are best-  
948 sampled, 1991.5 to 2011.5, gave very similar results, including a divergent continental sink ( $p=0.04$ ).



949

## 950 **Continental and Pan-Tropical Carbon Sink Estimates**

951 The *per unit area total net carbon sink* (in  $\text{Mg C ha}^{-1} \text{ yr}^{-1}$ ) for each time period in Table 1 (each  
952 decade between 1980 and 2010; and 2010-2015) is the sum of three components. The first  
953 component is the per unit area aboveground carbon sink from living trees and lianas with  $\text{DBH} \geq 100$   
954 mm. For Africa we use the per unit area net carbon sink values presented in this paper. For  
955 Amazonia, we use data in ref.<sup>6</sup>. For Southeast Asia, we use inventory data collected using similar  
956 standardised methods from 49 plots in ref.<sup>15</sup>. For each time window, we use all plots for which  
957 census dates overlap the period, weighted by the square root of plot area, as for the solid lines in  
958 Figure 1. The second component is the per unit area aboveground carbon sink from living trees and  
959 lianas with  $\text{DBH} < 100$  mm. This is calculated as 5.19%, 9.40% and 5.46% of the first component (i.e.  
960 aboveground carbon of large living trees) in Africa, Amazonia and Southeast Asia respectively<sup>13,74</sup>.  
961 The third component is the per unit area belowground carbon sink in live biomass, i.e. roots. This is  
962 calculated as 25%, 37% and 17% of the aboveground carbon of living trees with  $\text{DBH} \geq 100$  mm in  
963 Africa<sup>13</sup>, Amazonia<sup>6</sup> and Southeast Asia<sup>75</sup> respectively.

964

965 For each time period in Table 1 we calculated the *continental-scale total carbon sink* ( $\text{Pg C yr}^{-1}$ ) by  
966 multiplying the per unit area total net carbon sink described above by the area of intact forest on each  
967 continent at that time interval (in ha) reported in Extended Data Table 2. Decades are calculated from  
968 1990.01 to 1999.99. For comparability with previous continental-sink results, we used continental  
969 values of intact forest area for 1990, 2000 and 2010 as published in ref.<sup>1</sup>, i.e. total forest area minus  
970 forest regrowth. We used the 1990-2010 data to fit an exponential model for each continent and used  
971 this model to estimate intact forest area for 1980 and 2015.

972

973 Finally, in the main text we calculated the proportion of anthropogenic  $\text{CO}_2$  emissions removed by Earth's  
974 intact tropical forests, as the total pan-tropical carbon sink from Table 1 divided by the total anthropogenic

CO<sub>2</sub> emissions. Total anthropogenic CO<sub>2</sub> emissions are calculated as the sum of emissions from fossil fuel and land-use change and are estimated at 7.6 Pg C yr<sup>-1</sup> in the 1990s, 9.0 Pg C yr<sup>-1</sup> in the 2000s, and 11.1 Pg C yr<sup>-1</sup> in the 2010s (ref.<sup>21</sup>, assuming 1.7% growth in fossil fuel emissions in 2018 and 2019, and mean 2010-2017 land-use change emissions for 2018 and 2019).

979

## 980 **Carbon Sink from an Atmospheric Perspective**

To estimate the evolution of the carbon sink from an atmospheric perspective, we assumed that the contribution to the atmosphere from carbon gains are experienced immediately, while the contribution to the atmosphere from carbon losses must take into account the delay in decomposition of dead trees. We did this by calculating total forest carbon loss (Mg C ha<sup>-1</sup> yr<sup>-1</sup>) for each year between 1950-2015, using the mean 1983-2015 records from Figure 1 and assuming constant losses prior to 1983 (1.9 and 1.5 Mg C ha<sup>-1</sup> yr<sup>-1</sup> for Africa and Amazonia respectively). Then, for each focal year between 1950-2015, we calculated how much carbon was released to the atmosphere in the subsequent years as:  $y_t = x_0 \times e^{-0.17 \times (t-1)} - x_0 \times e^{-0.17 \times t}$ , where  $x_0$  is the total forest carbon loss of the focal year;  $y_t$  is the carbon released to the atmosphere at  $t$  years from the focal year; and -0.17 yr<sup>-1</sup> is a constant decomposition rate calculated for tropical forests in the Amazon<sup>45</sup>. For example, carbon loss was 1.95 Mg C ha<sup>-1</sup> in 1990 in African forests (Figure 1), from which 0.31 Mg C ha<sup>-1</sup> was released to the atmosphere in 1991; 0.26 Mg C ha<sup>-1</sup> in 1992; 0.22 Mg C ha<sup>-1</sup> in 1993; 0.07 Mg C ha<sup>-1</sup> in 2000 and 0.01 Mg C ha<sup>-1</sup> in 2010. Hence, of the full 1.95 Mg C ha<sup>-1</sup> dead tree biomass from 1990, ~50% was released to the atmosphere after 4 yrs, ~85% after 10 yrs, and ~97% after 20 years. Finally, for each year between 1983 and 2015, the total contribution to the atmosphere from carbon losses was calculated as the sum of all carbon contributions released at that year, from all total yearly forest carbon loss pools of the previous years. We then calculated decadal-scale mean contributions to the atmosphere from carbon losses, reported in the main text.

999

1000 **Predictor Variable Estimates, 1983-2014**

1001 For each census interval of each plot, we examined potential predictor variables that may explain the  
1002 long-term trends in carbon gains and carbon losses, reported in Extended Data Table 1 and main text  
1003 Table 2. First, the environmental conditions during the census interval; second the rate of change of  
1004 these parameters; and third forest attributes that may affect how different forests respond to the same  
1005 environmental change. The predictor variable estimates for each census need to avoid bias due to  
1006 seasonal variation, for example the intra-annual variability in atmospheric CO<sub>2</sub> concentration. We  
1007 therefore applied the following procedure to avoid seasonal variability impacts on long-term trends:  
1008 (i) the length of each focal census interval was rounded to the nearest complete year (e.g. a 1.1 year  
1009 interval became a 1 year interval); (ii) we computed dates that minimised the difference between  
1010 actual fieldwork dates and complete-year census dates, while ensuring that subsequent census  
1011 intervals of a plot do not overlap. The resulting sequence of non-overlapping census intervals was  
1012 used to calculate interval-specific means for each environmental predictor variable to remove  
1013 seasonal effects. The mean difference between the actual fieldwork dates and the complete-year  
1014 census dates is 0.01 decimal years.

1015  
1016 The first group of potential predictor variables, estimated for each census interval of each plot, are  
1017 theory-driven choices: atmospheric CO<sub>2</sub> concentration (CO<sub>2</sub>), mean annual temperature (MAT), and  
1018 drought intensity, which we quantified as maximum climatological water deficit (MCWD)<sup>14,20,76,77</sup>.

1019  
1020 *Atmospheric CO<sub>2</sub> concentration* (CO<sub>2</sub>, in ppm) is estimated as the mean of the monthly mean values  
1021 from the Mauna Loa record<sup>78</sup> over the census interval. While atmospheric CO<sub>2</sub> concentration is  
1022 highly correlated with time ( $R^2=0.98$ ), carbon gains are slightly better correlated with CO<sub>2</sub>  
1023 ( $R_{adj}^2=0.0027$ ) than with time ( $R_{adj}^2=0.0025$ ).

1024

1025 *Mean Annual Temperature* (MAT, in °C) was derived from the temporally resolved (1901-2015)  
1026 dataset of monthly mean temperature from the Climatic Research Unit (CRU TS version 4.03; ~3025  
1027 km<sup>2</sup> resolution; released 15 May 2019; <https://crudata.uea.ac.uk/cru/data/hrg/>)<sup>79</sup>. We downsampled the  
1028 data to ~1 km<sup>2</sup> resolution using the WorldClim dataset<sup>51,80</sup>, by subtracting the difference in mean  
1029 monthly temperature, and applying this monthly correction to all months<sup>81</sup>. We then calculated MAT  
1030 for each census interval of each plot using the downsampled monthly CRU record.

1031

1032 *Maximum Climatological Water Deficit* (MCWD, in mm) was derived from the ~3025 km<sup>2</sup>  
1033 resolution Global Precipitation Climatology Centre dataset (GPCC version 6.0) that includes many  
1034 more rain gauges than CRU in tropical Africa<sup>82,83</sup>. As GPCC ends in 2013 we combined it with  
1035 satellite-based Tropical Rainfall Measurement Mission data (TRMM 3B43 V7 product, ~757 km<sup>2</sup>  
1036 resolution)<sup>84</sup>. The fit for the overlapping time period (1998-2013) was used to correct the systematic  
1037 difference between GPCC and TRMM:  $GPCC' = a + b * GPCC$ , with GPCC' the adjusted GPCC  
1038 record and a and b different parameters for each month of the year and for each continent.  
1039 Precipitation was then downsampled to ~1 km<sup>2</sup> resolution using the WorldClim dataset<sup>51,80</sup>, by dividing  
1040 by the ratio in mean monthly rainfall, and applying this monthly correction to all months<sup>81</sup>. For each  
1041 census interval we extracted monthly precipitation values and estimated evapotranspiration (ET) to  
1042 calculate monthly Climatological Water Deficit (CWD), a commonly used metric of dry season  
1043 intensity for tropical forests<sup>14,76,77</sup>. Monthly CWD values were calculated for each subsequent series  
1044 of 12 months (complete years)<sup>77</sup>. Monthly CWD estimation begins with the wettest month of the first  
1045 year in the interval, and is calculated as 100 mm per month evapotranspiration (ET) minus monthly  
1046 precipitation (P). Then, CWD values for the subsequent 11 months were calculated recursively as:  
1047  $CWD_i = ET - P_i + CWD_{i-1}$ , where negative  $CWD_i$  values were set to zero<sup>77</sup> (no drought conditions).  
1048 This procedure was repeated for each subsequent complete 12 months. We then calculated the annual  
1049 MCWD as the largest monthly CWD value for every complete year within the census interval, with

1050 the MCWD of a census interval being the mean of the annual MCWD values within the census  
1051 interval. Larger MCWD indicates more severe water deficits.

1052

1053 We assume ET is 100 mm month<sup>-1</sup> on both continents, based on measurements from Amazonia<sup>76,77</sup>,  
1054 more limited measurements from West Africa summarized in ref.<sup>85</sup>, predictive skill<sup>86</sup>, and use in past  
1055 studies on both continents<sup>14,87</sup>. MCWD therefore represents a precipitation-driven dry season deficit,  
1056 as ET remains constant. An alternative assessment, using a data-driven ET product<sup>88,89</sup>, gave a mean  
1057 ET of 95 and 98 mm month<sup>-1</sup> for the African and Amazonian plot networks respectively. Using these  
1058 values did not affect the results.

1059

1060 To calculate the environmental change of potential predictor variables, CO<sub>2</sub>-change (in ppm yr<sup>-1</sup>),  
1061 MAT-change (in °C yr<sup>-1</sup>) and MCWD-change (in mm yr<sup>-1</sup>), we selected an optimum period over  
1062 which to calculate the change, derived empirically by assessing the correlation of carbon gains (all  
1063 plots, all censuses) with the change in each environmental variable, using linear mixed effects  
1064 models (lmer function in R, lme4 package<sup>72</sup>). The annualised change in the environmental variable  
1065 was calculated as the change between the focal interval and a prior interval (termed the baseline  
1066 period) with a lengthening time window ranging from 1 year through to 80 years prior to the focal  
1067 interval (i.e. 80 linear mixed effects models per variable). We calculated AIC for each model and  
1068 selected the interval length with the lowest AIC. Thus, MAT-change (in °C yr<sup>-1</sup>) = (MAT<sub>i</sub>-  
1069 MAT<sub>b</sub>)/(date<sub>i</sub>-date<sub>b</sub>), where MAT<sub>i</sub> is the MAT over the focal census interval calculated using the  
1070 procedure described above, MAT<sub>b</sub> is the MAT over a baseline period prior to the focal interval, date<sub>i</sub>  
1071 is the mid-date of the focal census interval and date<sub>b</sub> is the mid-date of the baseline period. The lmer  
1072 results show that the baseline period for MAT-change is 5 years and for CO<sub>2</sub>-change it is 56 years,  
1073 while MCWD showed no clear trend, so MCWD-change was not included in the models (see  
1074 Extended Data Figure 3). All three results conform to *a priori* theoretical expectations. For CO<sub>2</sub> a

1075 maximum response to an integrated 56 years of change is expected because forest stands will  
1076 respond most strongly to CO<sub>2</sub> when most individuals have grown under the new rapidly changing  
1077 condition, which should be at its maximum at a time approximately equivalent to the carbon  
1078 residence time of a forest stand<sup>30,90</sup> (mean of 62 years in this dataset). For MAT, 5 years is consistent  
1079 with experiments showing temperature acclimation of leaf- and plant-level photosynthetic and  
1080 respiration processes over half-decadal timescales<sup>31,91</sup>. MCWD has no overall trend suggesting that  
1081 once a drought ends, its impact on tree growth fades rapidly, as seen in other studies<sup>14,92</sup>. Also in the  
1082 moist tropics wet-season rainfall is expected to re-charge soil water, hence lagged impacts of  
1083 droughts are not expected.

1084

1085 We calculated estimates of two forest attributes that may alter responses to environmental change as  
1086 potential predictor variables: Wood Density (WD) and Carbon Residence Time (CRT). In intact old-  
1087 growth forests, mean WD (in g cm<sup>-3</sup>) is inversely related to resource availability<sup>28,93,94</sup>, as is seen in  
1088 our dataset (carbon gains and plot-level mean WD are negatively correlated, Extended Data Figure  
1089 4). WD is calculated for each census interval in the dataset, as the mean WD of all trees alive at the  
1090 end of the census interval, to be consistent with the previous Amazon analysis<sup>6</sup>. Carbon residence  
1091 time (CRT, in yrs) is a measure of the time that fixed carbon stays in the system. CRT is a potential  
1092 correlate of the impact of past carbon gains on later carbon losses<sup>30</sup>. To avoid circularity in the  
1093 models, the equation used to calculate CRT differed depending on the response variable. If the  
1094 response variable is carbon loss, the CRT equation is based on gains:  $CRT = AGC / \text{gains}$ , with AGC  
1095 for each interval based on AGC at the end of the interval, and the gains for each interval calculated  
1096 as the mean of the gains in the interval and the previous intervals (i.e. long-term gains). If the  
1097 response variable is carbon gains, the CRT equation is based on losses:  $CRT = AGC / \text{losses}$ . The  
1098 equation employed for use in the carbon loss model (based on gains) is the standard formula used to  
1099 calculate CRT and is retained in the minimum adequate model (see below and Table 2). The non-

1100 standard CRT equation (based on losses) used in the carbon gain model is not retained in the  
1101 minimum adequate model (see below).

1102  
1103 **Statistical modelling of the Carbon Gain, Loss and Sink Trends**

1104 We first constructed two models including those environmental drivers exhibiting long-term change  
1105 that impact theory-driven models of photosynthesis and respiration as predictor variables: CO<sub>2</sub>,  
1106 MAT, and MCWD. One model had carbon gains as the response variable, the other had carbon  
1107 losses as the response variable (both in Mg C ha<sup>-1</sup> yr<sup>-1</sup>). Models were fitted using the lme function in  
1108 R, with maximum likelihood (NLME package<sup>95</sup>). All census intervals within all plots were used,  
1109 weighted by plot size and census length (using equation 3 above). Plot identity was included as a  
1110 random effect, i.e. assuming that the intercept can vary randomly among plots. All predictor  
1111 variables in the models were scaled without centering (scale function in R, RASTER package<sup>62</sup>).  
1112 Carbon gain values were normally distributed but carbon loss values required a power-law  
1113 transformation ( $\lambda = 0.361$ ) to meet normality criteria. Multi-parameter models are: carbon gains =  
1114  $\text{intcp} + a \times \text{CO}_2 + b \times \text{MAT} + c \times \text{MCWD}$  (model 1); carbon losses =  $\text{intcp} + a \times \text{CO}_2 + b \times \text{MAT} +$   
1115  $c \times \text{MCWD}$  (model 2); where intcp is the estimated model intercept, and a, b, and c are model  
1116 parameters giving the slope of relationships with environmental predictor variables. For multi-  
1117 parameter model outputs see Extended Data Table 1, for single-parameter relationships, Figure 2.

1118  
1119 The second pair of models include the same environmental predictors (CO<sub>2</sub>, MAT, MCWD), plus  
1120 their rate of change (CO<sub>2</sub>-change, MAT-change, but not MCWD-change as explained above), and  
1121 forest attributes that may alter how forests respond (WD, CRT), as described above. We also  
1122 evaluated the possible inclusion of a differential continent effect of each variable in the full model.  
1123 We first constructed models with only a single predictor variable, and allowed different slopes in  
1124 each continent. Next, if removal of the continent-specific slope (using stepAIC function in R, MASS

1125 package<sup>96</sup>) decreased model Akaike Information Criterion (AIC) then the continent-specific slope  
 1126 was not included in the full model for that variable. Only MCWD showed a significant differential  
 1127 continent-specific slope. This implies that forests on both continents have common responses to CO<sub>2</sub>,  
 1128 CO<sub>2</sub>-change, MAT, MAT-change, WD and CRT, but respond differently to differences in MCWD.  
 1129 This is likely because wet-adapted species are much rarer in Africa than in Amazonia as a result of  
 1130 large differences in past climate variation<sup>34</sup>. Lastly, we allowed different intercepts for the two  
 1131 continents to potentially account for differing biogeographical or other continent-specific factors. For  
 1132 the carbon loss model, we applied the same continent-specific effects for slope as for the carbon gain  
 1133 model. Carbon loss values were transformed using a power-law transformation ( $\lambda = 0.361$ ) to meet  
 1134 normality criteria.

1135

1136 For both carbon gains and losses we parameterized a global model including the significant  
 1137 continent-specific effect of MCWD, selecting the most parsimonious simplified model using all-  
 1138 subsets regression<sup>97,98</sup>. To do so, we first generated a set of models with all possible combinations  
 1139 (subsets) of fixed effect terms in the global model using the dredge function of the MuMIn package  
 1140 in R<sup>99</sup>. We then chose the best-ranked simplified model based on the AICc criterion, hereafter called  
 1141 “minimum adequate carbon gain/loss model”, reported in Table 2. The minimum adequate models  
 1142 are: carbon gains =  $\text{intcp} \times \text{continent} + a \times \text{CO}_2\text{-change} + b \times \text{MAT} + c \times \text{MAT-change} +$   
 1143  $d \times \text{MCWD} \times \text{continent} + e \times \text{WD}$  (model 3); carbon losses =  $\text{intcp} + a \times \text{CO}_2\text{-change} + b \times \text{MAT-change}$   
 1144  $+ c \times \text{MCWD} + d \times \text{CRT}$  (model 4). WD was retained in the carbon gain model, likely because growth  
 1145 is primarily impacted by resource availability, while CRT was retained in the carbon loss model,  
 1146 likely because losses are primarily impacted by how long fixed carbon is retained in the system.

1147

1148 Table 2 presents model coefficients of the best-ranked gain model and best-ranked loss model  
 1149 selected using all-subsets regression. These best-ranked gain and loss models have weights of 0.310



1150 and 0.132 respectively, which is almost double the weight of the second ranked models (0.152 and  
1151 0.075 respectively). In Supplementary Table 2 we also used the model.avg function of the MuMIn  
1152 package to calculate a weighted mean of the coefficients of the best-ranked models together  
1153 representing a cumulative weight-sum of 0.95 (i.e. a 95% confidence subset). Supplementary Table 2  
1154 (model-averaged) and main text Table 2 (best-ranked) model parameters are very similar.  
1155 Supplementary Tables 3 and 4 report the complete sets of carbon gains and loss models that  
1156 contribute to the model average results.

1157

1158 The model-average results show the same continental differences in sensitivity to environmental  
1159 variables as the best-ranked models. From 2000 to 2015, carbon gains increased due to CO<sub>2</sub>-change  
1160 (+3.7% in both the averaged and the best-ranked models, both continents), while temperature rises  
1161 led to a decline in gains, which especially had an effect in the Amazon (-1.14% and -1.07% due to  
1162 MAT and MAT-change together in the averaged and best-ranked model respectively). Finally, both  
1163 models result in similar predictions of the net carbon sink over the 1983-2040 period: the future net  
1164 sink trend in Africa is -0.004 and -0.003 in the best-ranked and averaged models respectively; in  
1165 Amazonia the future net sink trend is -0.013 and -0.011 in the best-ranked and averaged models  
1166 respectively. The Amazon sink reaches zero in 2041 using model-averaged parameters compared to  
1167 2035 using the best-ranked models.

1168

1169 **Estimating Future Predictor Variables to 2040**

1170 To calculate future modelled trends in carbon gains and losses (Figure 3), we first estimated annual  
1171 records of the predictor variables (CO<sub>2</sub>-change, MAT, MAT-change, MCWD, WD and CRT) to  
1172 2040 (Extended Data Figure 5).

1173

To do so we first calculated annual records for the period of the observed trends for each plot location (i.e. from 1983-2014 in Africa and 1983-2011.5 in Amazonia). For CO<sub>2</sub>-change, MAT, MAT-change and MCWD we extracted monthly records as described in section Predictor Variable Estimates (above). For WD and CRT we interpolated to a 0.1-yr period within each census interval (as in Figure 1). Then, we calculated the mean annual value of each predictor variable from the 244 plot locations in Africa, and separately the mean annual value of each predictor variable from the 321 plot locations in Amazonia (i.e. solid lines in ED Figure 5). For each predictor variable, we calculated annual records of upper and lower confidence intervals by respectively adding and subtracting  $2\sigma$  to the mean of each annual value (shaded area in ED Figure 5).

Secondly, for each predictor variable we parameterised a linear model for each continent using the annual records for the period of the observed trends. Then for each predictor variable, the continent-specific linear regression models were used to estimate predictor variables for each plot location from 2014 to 2040 in Africa and from 2011.5 to 2040 in the Amazon (dotted lines in Extended Data Figure 5). For each predictor variable, we calculated annual records of upper and lower confidence intervals by respectively adding and subtracting  $2\sigma$  to the slope of each linear model (shaded area around dotted lines in ED Figure 5).

### **Estimating Future Carbon Gain, Loss and Net Carbon Sink**

We used the minimum adequate models (Table 2) to predict annual records of carbon gain, carbon loss and the carbon sink for the plot networks in Africa and Amazonia over the period 1983 through to 2040 (Figure 3). We extracted fitted carbon gain and loss values using the mean annual records for each predictor variable (predictSE.lme function, AICcmodavg package<sup>100</sup>). Upper and lower confidence intervals were calculated accounting for uncertainties in the model (both fixed and random effects) and predictor variables using the  $2\sigma$  upper and lower confidence interval for each

1199 predictor variable (using predictSE.lme). Finally the net carbon sink was calculated by subtracting  
1200 the losses from the gains. To obtain sink values in the future in Table 1, annual per unit area sink  
1201 predictions, from Figure 3, were averaged over each decade and multiplied by the future forest area,  
1202 as described above.

1203

1204 To test the sensitivity of the future predictions in Figure 3, we reran the analysis by modifying future  
1205 trajectories of predictor variables one at a time, while keeping all others the same, to assess the mean  
1206 C sink over 2010-15 and 2030 (averaging at 2030 is not necessary as trends in MAT-change and  
1207 MCWD, which largely drive modelled inter-annual variability, are estimated as smooth trends in the  
1208 future). For each predictor variable, we explored potential impacts of the likely bounds of possibility,  
1209 (i) by taking the steepest slope of either continent from the extrapolated trends, doubling this slope  
1210 and applying it on both continents; and (ii) by taking the steepest slope of either continent from the  
1211 extrapolated trends, taking the opposite of this slope and applying it on both continents. These  
1212 bounds represent deviations of >2 sigma from observed trends. Change in MAT also alters MAT-  
1213 change, so we present the sensitivity of both parameters together.

1214

1215 Additionally, for CO<sub>2</sub>-change and MAT, we also calculated future slopes under three future  
1216 Representative Concentration Pathway (RCP) scenarios<sup>38</sup> with different radiative forcing in 2100:  
1217 RCP2.6, 4.5, and 8.5. Future RCP CO<sub>2</sub>-change slopes (ppm yr<sup>-1</sup>) were calculated using RCP CO<sub>2</sub>  
1218 concentration data for the years between 2015 and 2030 inclusive. Future RCP MAT and MAT-  
1219 change slopes were obtained from plot-specific MAT values extracted from downscaled 30 seconds  
1220 resolution data for current<sup>80</sup> and future<sup>51</sup> climate from WorldClim, and averaged over 19 CMIP5  
1221 models. We subtracted the mean 2040-2060 climate MAT (i.e. 2050) from the mean 1970-2000  
1222 climate MAT (i.e. 1985), divided by 65 years to give the annual rate of change. We then calculated a  
1223 mean slope over all plots per continent. Finally, to avoid mismatches between RCP-derived values of

CO<sub>2</sub> and MAT and the observed records we removed any difference in intercept between the RCP trends and observed trends, so the RCP trends were a continuation of the end-point of the observed trajectory in 2015. We did not estimate the sensitivity of MCWD under the RCP scenarios, because the CMIP5 model means do not show drought trends for our forest plot networks, unlike rain gauge data for the recent past, and thus would show little or no sensitivity to MCWD. For each modified slope, Supplementary Table 5 reports the absolute decline in the sink in each continent in 2030 compared to the 2010-15 mean sink. This shows that the future sink strength is sensitive to future environmental conditions, but within both RCP scenarios and our bounds of possibility we show a decline in the sink strength in both continents over the 2020s.

1233

**Data and Code Availability**

Source data and R-code to generate figures and tables are available from:  
[http://dx.doi.org/10.5521/Forestplots.net/2019\\_1](http://dx.doi.org/10.5521/Forestplots.net/2019_1)

1237

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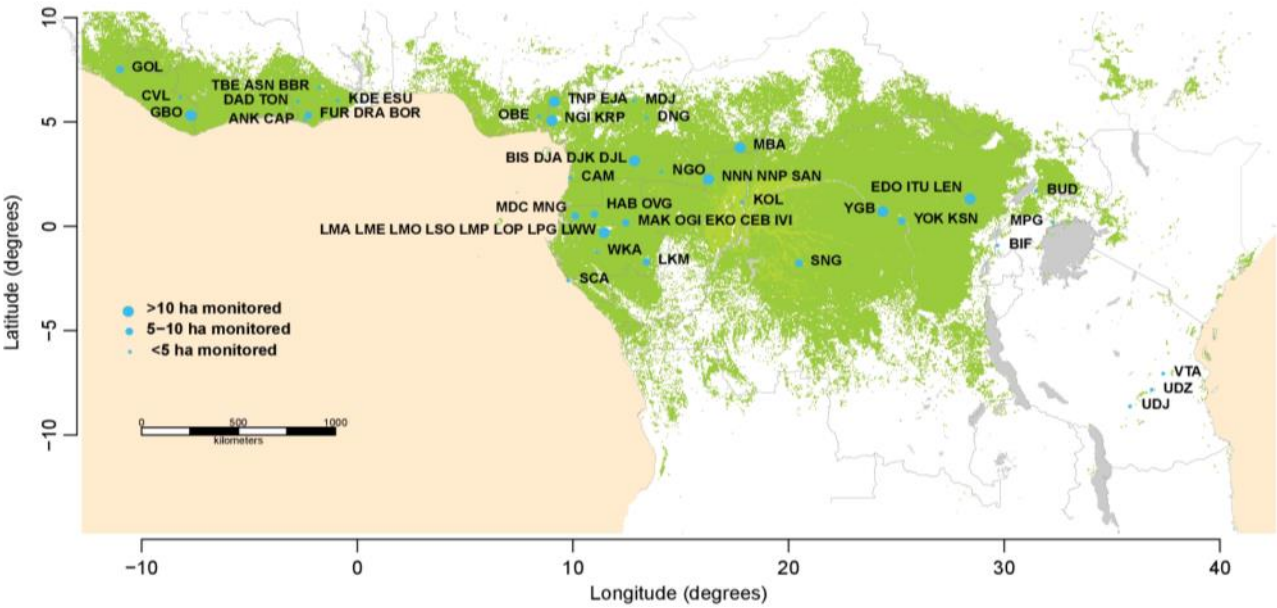
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1372 **Author Information**

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1374 authors declare no competing financial interests. Supplementary Information is available online for  
1375 this paper.

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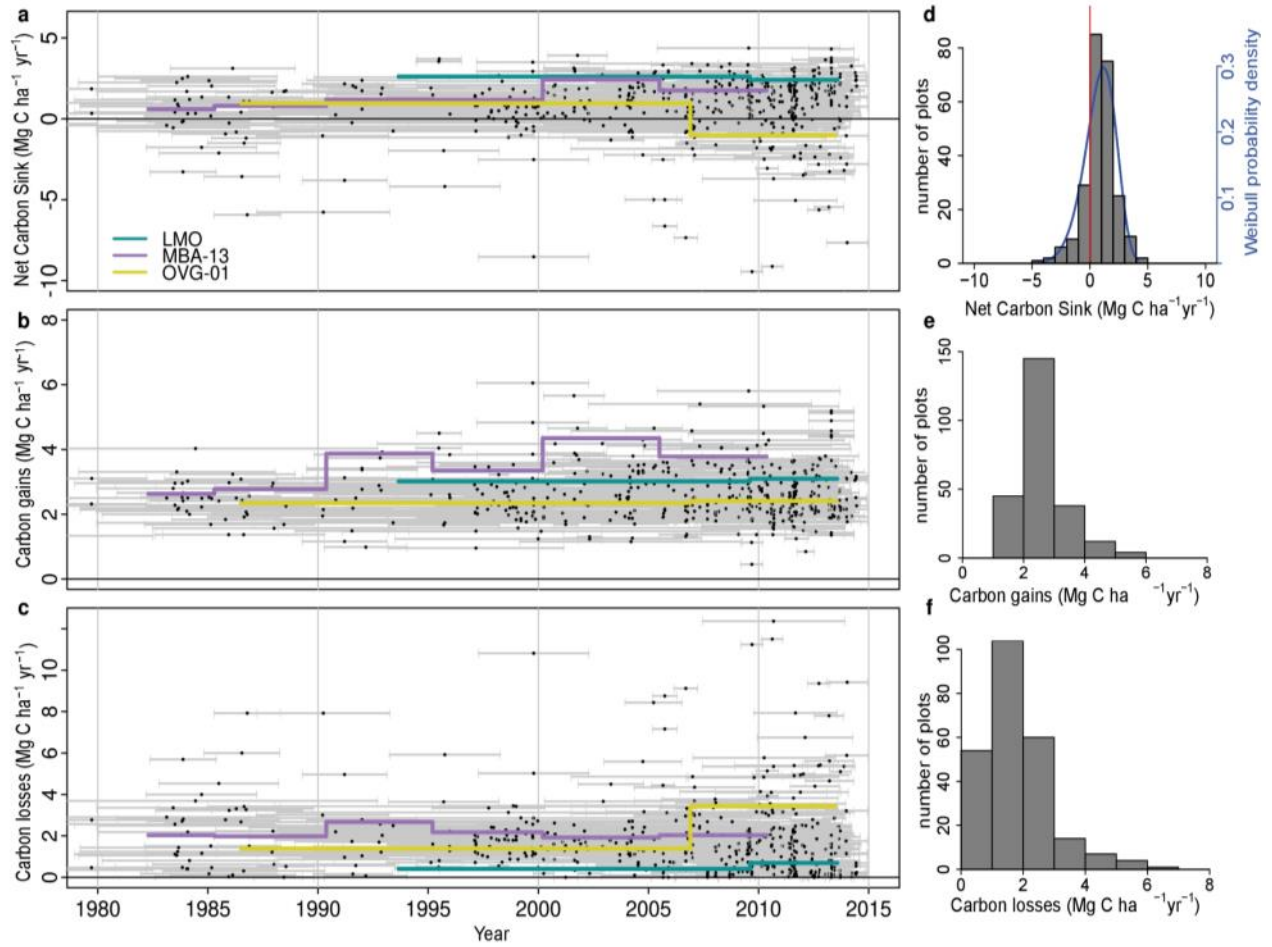
1377 **Extended Data Figures**



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1379 **Extended Data Figure 1. Map showing the locations of the 244 plots included in this study.**

1380 Dark green represents all lowland closed-canopy forests, submontane forests and forest-agriculture  
1381 mosaics; light green shows swamp forests and mangroves<sup>101</sup>, blue circles represent plot clusters,  
1382 referred to by three-letter codes (see Supplementary Table 1 for the full list of plots). Clusters <50  
1383 km apart are shown as one point for display only, with the circlesize corresponding to sampling  
1384 effort in terms of hectares monitored.



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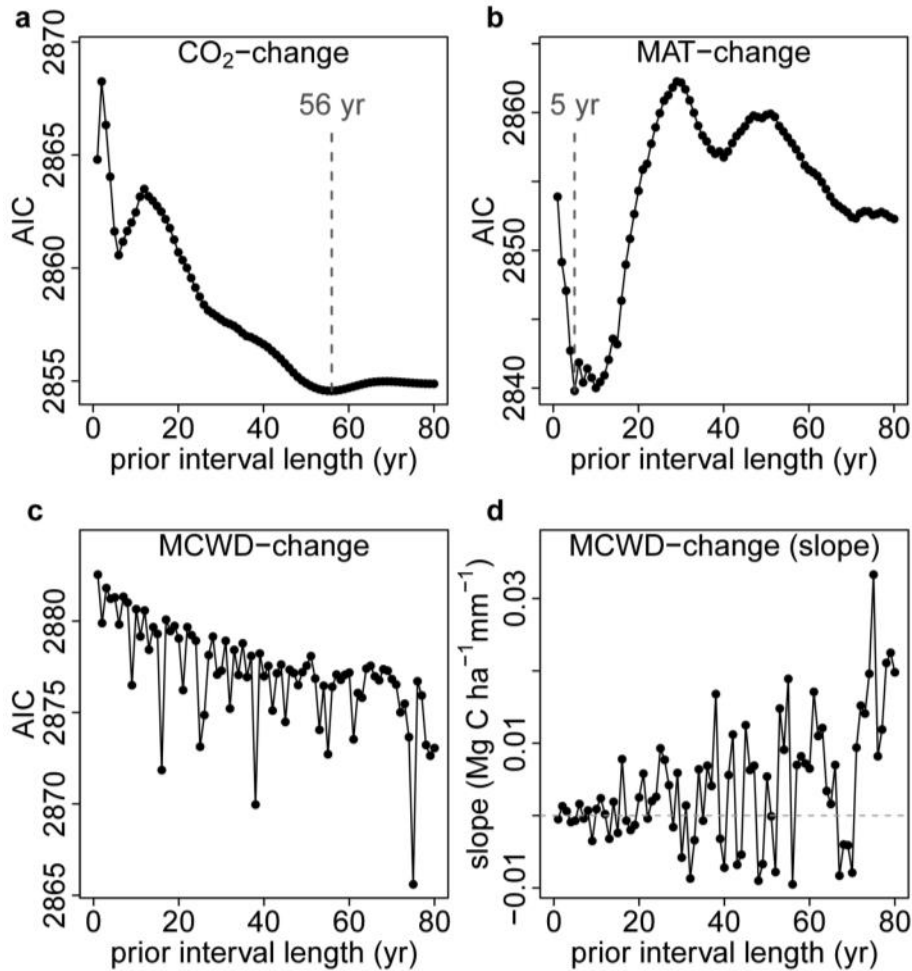
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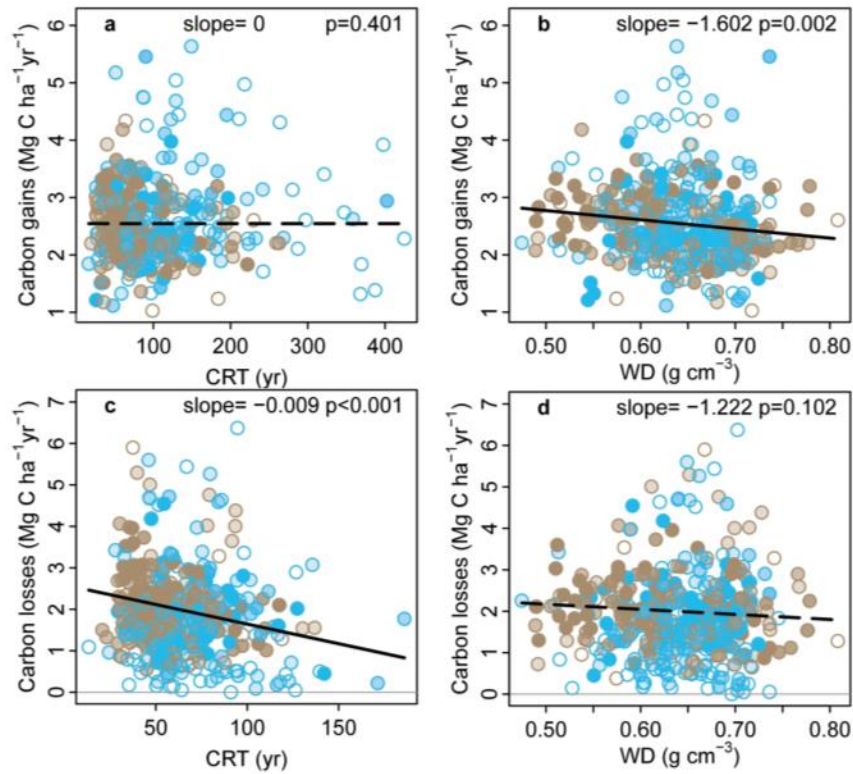
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**Extended Data Figure 2. Long-term above-ground carbon dynamics of 244 African intact tropical forest inventory plots.** Points in the scatterplots indicate the mid-census interval date, with horizontal bars connecting the start and end date for each census interval for net aboveground biomass carbon change (a), carbon gains (from woody production from tree growth and newly recruited stems) (b), and carbon losses (from tree mortality) (c). Examples of time series for three individual plots are shown in purple, yellow and green. Associated histograms show the distribution of the plot-level net aboveground biomass carbon (d) (with a three-parameter Weibull probability density distribution fitted in blue, showing the carbon sink is significantly larger than zero; one-tail t-test:  $p < 0.001$ ), carbon gains (e), and carbon losses (f).



**Extended Data Figure 3. Akaike's Information Criterion (AIC) from correlations between the carbon gain in tropical forest inventory plots and changes in either atmospheric CO<sub>2</sub>, temperature (as MAT) or drought (as MCWD), each calculated over ever-longer prior intervals.** Panels show AIC from linear mixed effects models of carbon gains from 565 plots and corresponding, atmospheric CO<sub>2</sub> (CO<sub>2</sub>-change) (a), Mean Annual Temperature (MAT-change) (b), and Maximum Climatological Water Deficit (MCWD-change) (c). For CO<sub>2</sub> the AIC minimum was observed when predicting the carbon gain from the change in CO<sub>2</sub> calculated over a 56 year long prior interval length. We use this length of time to calculate our CO<sub>2</sub>-change parameter. Such a value is expected because forest stands will respond most strongly to CO<sub>2</sub> when most individuals have grown under the new rapidly changing condition, which should be at its maximum at a time approximately equivalent to the carbon residence time of a forest stand<sup>30,90</sup> (mean of 62 years in this

pooled African and Amazonian dataset). For MAT the AIC minimum was 5 years, which we use as the prior interval to calculate our MAT-change parameter. This length is consistent with experiments showing temperature acclimation of leaf- and plant-level photosynthetic and respiration processes over approximately half-decadal timescales<sup>31,91</sup>. For MCWD the AIC minimum is not obvious, while the slope of the correlation, shown in panel (d), shows no overall trend and oscillates between positive or negative values, meaning there is no relationship between carbon gains and the change in MCWD over intervals longer than 1 year; thus MCWD-change is not included in our models. This result suggests that once a drought ends, its impact on tree growth fades rapidly, as seen in other studies<sup>14,92</sup>. Also in the moist tropics wet-season rainfall is expected to re-charge soil water, hence lagged impacts of droughts are not expected.



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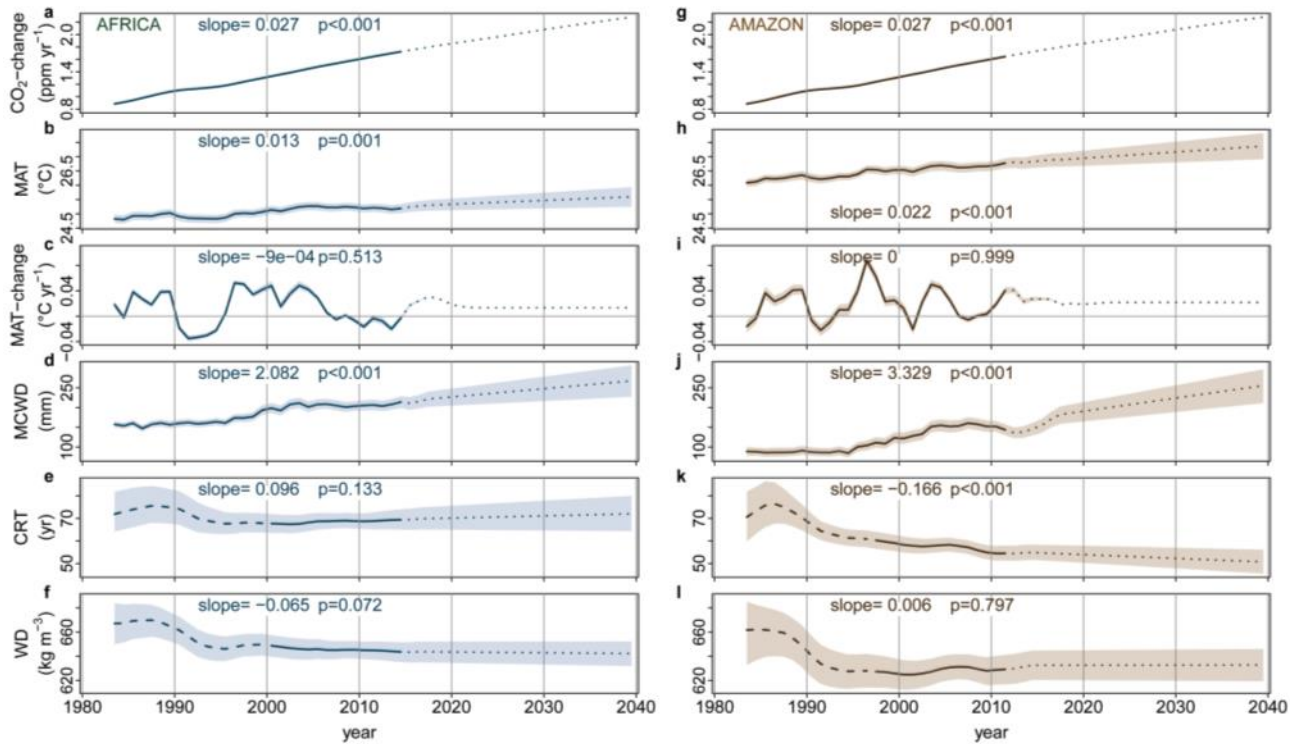
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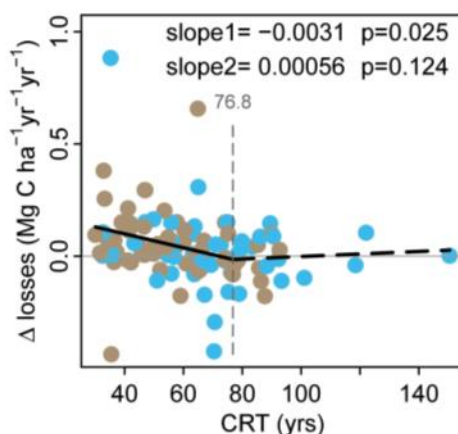
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**Extended Data Figure 4. Potential forest dynamics-related drivers of carbon gains and losses in structurally intact African and Amazonian tropical forest inventory plots.** The aboveground carbon gains, from woody production (**a-b**), and aboveground carbon losses, from tree mortality (**c-d**), are plotted against the carbon residence time (CRT), and wood density (WD), for African (blue) and Amazonian (brown) inventory plots. Linear mixed effect models were performed with census intervals ( $n=1566$ ) nested within plots ( $n=565$ ) to avoid pseudo-replication, using an empirically derived weighting based on interval length and plot area (see methods). Significant regression lines for the complete dataset are shown as a solid line; non-significant regressions as a dashed line. Each dot represents a time-weighted mean plot-level value; transparency of the inner part of the dot represents total monitoring length, with empty circles corresponding to plots monitored for  $\leq 5$  years and solid circles for plots monitored for  $>20$  years. Carbon loss data are presented untransformed for comparison with carbon gains; linear mixed effects models on transformed data to fit normality assumptions do not change the significance of the results. Note, CRT is calculated differently for the carbon gains and losses models (see methods).



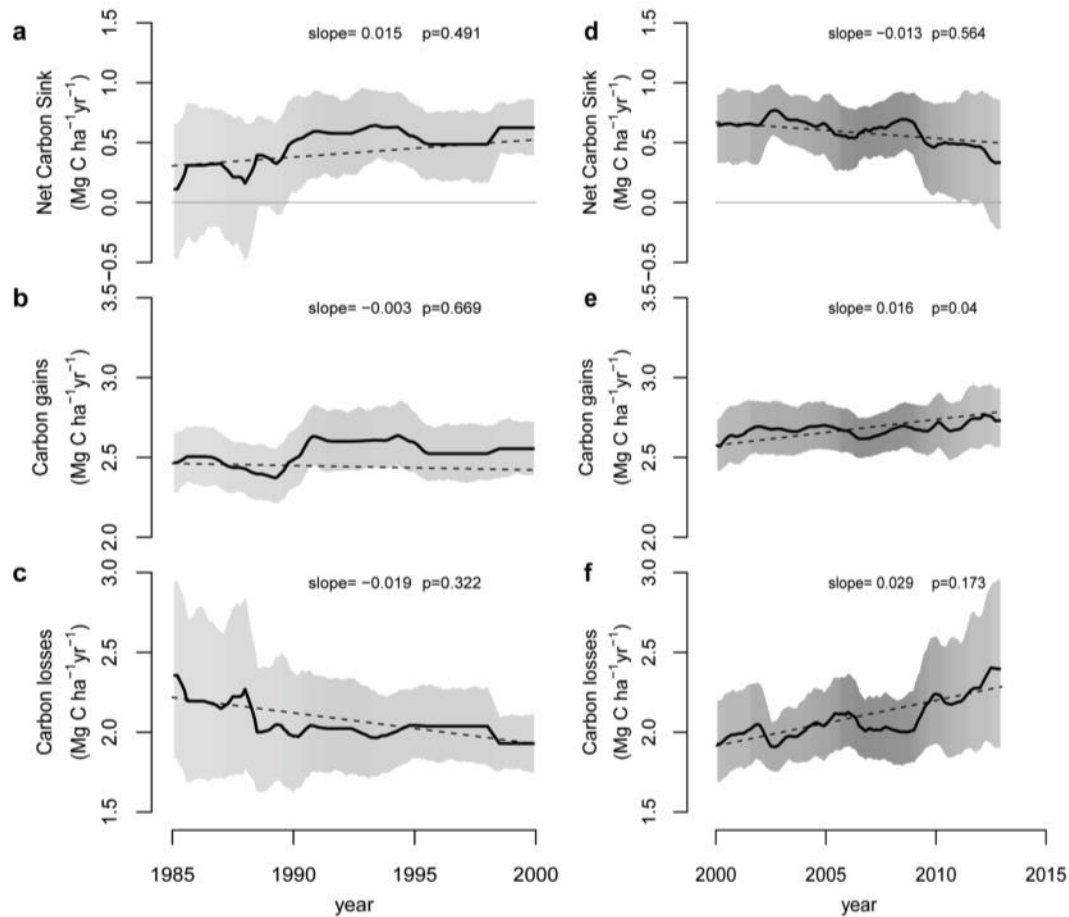
**Extended Data Figure 5. Trends in predictor variables used to estimate long-term trends in above-ground carbon gains, carbon losses and the resulting net carbon sink in African and Amazonian intact tropical forest plot networks.** Mean annual CO<sub>2</sub>-change (a), MAT (b), MAT-change (c), MCWD (d), CRT (e), and WD (f) for African plot locations in blue, and corresponding Amazon plots locations in brown (g-l). Solid lines for CO<sub>2</sub>-change, MAT, MAT-change, MCWD represent observational data, and solid lines for CRT and WD represent plot means and a time window where >75% of the plots were monitored, long-dashed lines are plot means were <75% of plots were monitored. Dotted lines are future values estimated from linear trends on the 1983-2014 (Africa) or 1983-2011 (Amazon) data (slope and p-value reported in each panel), see methods for details. Upper and lower confidence intervals (shaded area) for the past (Africa: 1983-2014; Amazonia: 1983-2011) are calculated by respectively adding and subtracting 2σ to the mean of each annual value. Upper and lower confidence intervals for the future were estimated by adding and subtracting 2σ from the slope of the regression model.



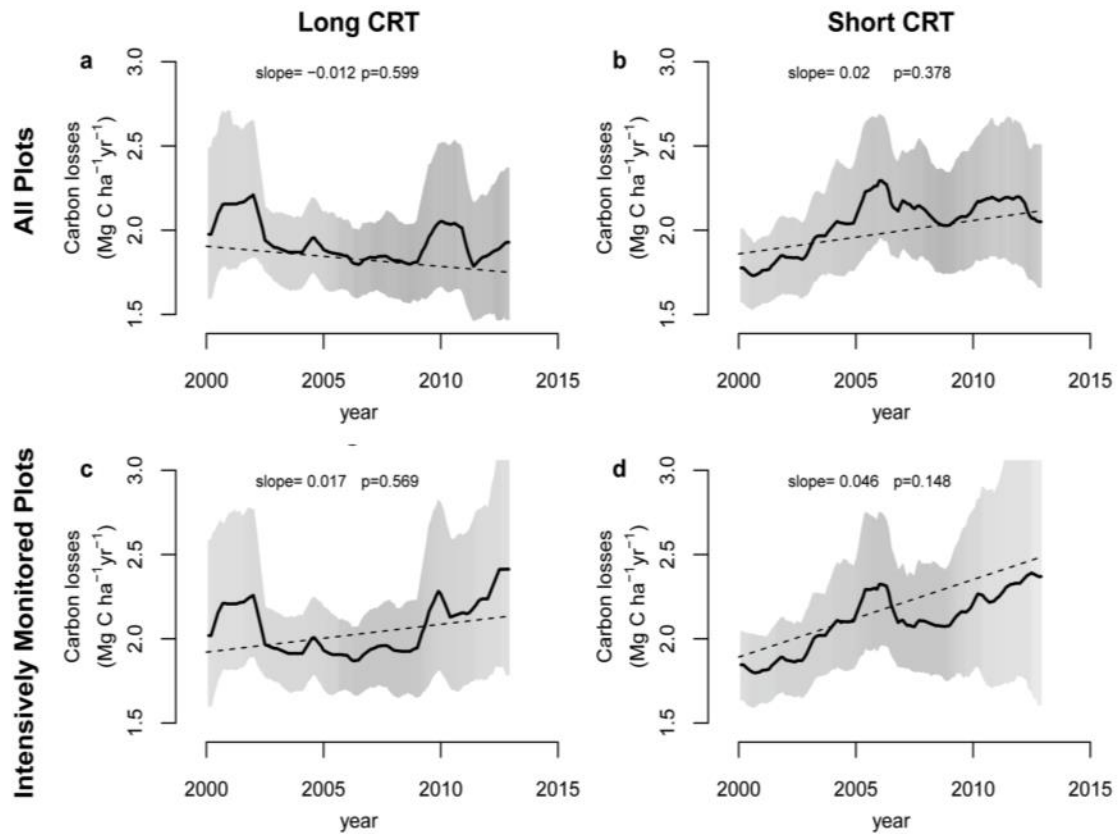


**Extended Data Figure 6. The change in carbon losses versus carbon residence time (CRT) of inventory plots in Africa and Amazonia.** For plots with two census intervals, we calculated the change in carbon losses ( $\Delta\text{losses}$ , in  $\text{Mg C ha}^{-1} \text{ yr}^{-1} \text{ yr}^{-1}$ ) as the carbon losses ( $\text{Mg C ha}^{-1} \text{ yr}^{-1}$ ) of the second interval minus the carbon losses of the first interval, divided by the difference in mid-interval dates. For plots with more than two intervals, we calculated the change in carbon losses for each pair of subsequent intervals, then calculated the plot-level mean over all pairs, weighted by the time length between mid-interval dates. This analysis includes only plots with at least two census intervals and monitored for  $\geq 20$  years (i.e. roughly one-third of the mean CRT of the pooled African and Amazon dataset;  $n = 116$ ). Breakpoint regression was used to assess the CRT length below which forest carbon losses begin to increase. Plots with  $\text{CRT} < 77$  years show a recent long-term increase in carbon losses, longer CRT plots do not. Blue points are African plots, brown points are Amazonian plots.





**Extended Data Figure 7. Trends in African tropical forest net aboveground live biomass carbon, carbon gains and carbon losses, calculated for the last 15 years of the twentieth century (left panels a-c) and the first 15 years of the twenty-first century (right panels d-f).** Plots were selected from the full dataset if their census intervals cover at least 50% of the respective time windows, i.e. they are intensely monitored ( $n=56$  plots for 1985-2000, and  $n=134$  plots for 2000-2015, respectively). Solid lines show mean values, shading corresponds to the 95% CI, as calculated in Figure 1. Dashed lines, slopes and p-values are from linear mixed effects models, as in Figure 1. The data shows a difference compared to Figure 1, notably the sink decline after ~2010 driven by rising carbon losses. This is because in Figure 1 we include all available plots over the 1983-2015 window, which includes clusters of plots monitored *only* in the 2010s that had low carbon loss and high carbon sink values.



**Extended Data Figure 8. Twenty-first century trends in aboveground biomass carbon losses from African tropical forest inventory plots with either long (left panels) or short (right panels) carbon residence time.** Upper panels include all plots, i.e. as in Figure 1, but split into a long-CRT group (a), and a short-CRT group (b), each containing half the 244 plots. Lower panels restrict plots to those spanning >50% of the time window, i.e. intensively monitored plots, as in Extended Data Figure 7, but split into a long-CRT group (c), and a short-CRT group (d), each containing half the 134 plots. Solid lines indicate mean values, shading the 95% CI, as for Figure 1. Dashed lines, slopes and p-values are from linear mixed-effects models, as for Figure 1. Carbon losses increase at a higher rate in the short-CRT than the long-CRT group of plots, in both datasets, although this increase is not statistically significant.

1490 **Extended Data Tables**

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1492 **Extended Data Table 1.** Models to predict carbon gains and losses in African and Amazonian  
1493 tropical forests, including only environmental variables, showing long-term trends that impact  
1494 theory-driven models of photosynthesis and respiration. Significant values in bold.

Carbon gains, Mg C ha <sup>-1</sup> yr <sup>-1</sup>				
Predictor variable	Parameter value	Standard Error	t-value	p-value
(Intercept)	4.694	0.739	6.354	0.000
CO <sub>2</sub> (ppm)	<b>0.005</b>	0.001	3.196	0.001
MAT (°C)	<b>-0.143</b>	0.021	-6.844	0.000
MCWD (mm x1000)	<b>-1.232</b>	0.210	-5.878	0.000
Carbon losses, Mg C ha <sup>-1</sup> yr <sup>-1</sup> *				
Predictor variable	Parameter value	Standard Error	t-value	p-value
(Intercept)	0.926	1.854	0.500	0.617
CO <sub>2</sub> (ppm)	0.004	0.004	0.947	0.344
MAT (°C)	-0.011	0.044	-0.249	0.804
MCWD (mm x1000)	-0.498	0.505	-0.985	0.325

1495 \* carbon loss values were normalized via power-law transformation,  $\lambda = 0.361$ .

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1497 **Extended Data Table 2.** Forest area estimates used to calculate total continental forest sink.

Period	intact forest area (Mha)*			
	Africa	Amazon	Southeast Asia	Pan-tropics
1980	671.5	958.3	233.6	1863.4
1985	634.3	921.1	207.4	1762.8
1990	600.2	885.2	190.6	1676.0
1995	565.9	851.1	163.5	1580.5
2000	531.8	817.2	136.9	1485.9
2005	504.8	784.5	129.2	1418.5
2010	477.8	756.3	118.4	1352.5
2015	450.5	726.7	101.5	1278.7
2020	425.5	698.5	90.1	1214.2
2025	402.0	671.5	80.0	1153.4
2030	379.7	645.4	71.0	1096.1
2035	358.6	620.4	63.0	1042.1
2040	338.8	596.4	56.0	991.1

\* Intact forest area for 1990, 2000 and 2007 is published in ref.1 (i.e. the total forest area minus forest regrowth). To estimate intact forest area for the other years in this table, we fitted exponential models for each continent using the published data.

1498